ANALYSIS OF DESIGN ARTIFACTS IN PLATFORM-BASED MARKETS

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To my mentor and inspiration, Dr C.B.Satpathy.

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ABSTRACT

Pamuru Subramanya Rama, Vandith Ph.D., Purdue University, August 2020. Analysis of Design Artifacts in Platform-based Markets. Major Professor: Karthik Kannan.

Digitization has led to emergence of many platforms-based markets. In this dissertation I focus on three different design problems in these markets. The first essay relates to augmented-reality platforms. Pokémon Go, an augmented-reality technology-based game, garnered tremendous public interest upon release with an average of 20 million active daily users. The game combines geo-spatial elements with gamification practices to incentivize user movement in the physical world. This work examines the potential externalities that such incentives may have on associated businesses. Particularly, we study the impact of Pokémon Go on local restaurants using online reviews as a proxy for consumer engagement and perception. We treat the release of Pokémon Go as a natural experiment and study the post-release impact on the associated restaurants. We find that restaurants located near an in-game artifact do indeed observe a higher level of consumer engagement and a more positive consumer perception as compared with those that have no in-game artifacts nearby. In addition, we find that the heterogeneous characteristics of the restaurants moderate the effect significantly. To the best of our knowledge, this study is the first to examine the economic implications of augmented-reality applications. Thereby, our research lays the foundations for how augmented-reality games affect consumer economic behavior. This work also builds insights into the potential value of such associations for business owners and policymakers.

The second essay focuses on the platform design problem in sponsored seaerch ad-market.Recent advances in technology have reduced frictions in various markets. In this research, we specifically investigate the role of frictions in determining the efficiency and bidding behavior in a generalized second price auction (GSP) – the most preferred mechanism for sponsored search advertisements. First, we simulate computational agents in the GSP setting and obtain predictions for the metrics of interest. Second, we test these predictions by conducting a human-subject experiment. We

find that, contrary to the theoretical prediction, the lower-valued advertisers (who do not win the auction) substantially overbid. Moreover, we find that the presence of market frictions moderates this phenomenon and results in higher allocative efficiency. These results have implications for policymakers and auction platform managers in designing incentives for more efficient auctions.

The third essay is about user-generated content platforms. These platform utilize various gamification strategies to incentivize user contributions. One of the most popular strategy is to provide platform sponsorships like a special status. Previous literature has extensively studied the impact of having these sponsorships user contributions. We specifically focus on the impact of losing such elite status. Once their contributions to the platform reduce in volume, elite users lose status. Using a unique empirical strategy we show that users continue to contribute high quality reviews, even though they lose their status. We utilize NLP to extract various review characteristics including sentiment and topics. Using an empirical strategy, we find that losing status does not modify the topic of the reviews written by the users, on average.

1. INTRODUCTION

In the past decade, digital platforms have experienced significant growth in terms of adoption, diversity and innovation. There are several reasons for the growth of platforms, including increase in internet adoption, growth of cloud computing, increasing mobile computing devices, and emergence of newer business models to monetize customers. Moreover, this phenomenon has been accelerated further by the inflection of Machine Learning and Artificial Intelligence literature in practice. Currently, platform companies have a market capitalization of \$2.6 trillion and have a wide range on impact on businesses, consumers, and workers. Platform economy has disrupted various domains of businesses leading to online ad-market places like Google and Facebook, sharing economies like Airbnb and Uber, and crowdfunding platforms like Kickstarter and Indiegogo, to name a few. Traditional literature on platforms has focused on equilibrium analysis of multi-sided platforms, mechanism design, and incentive structures. In this dissertation, I focus on design artifacts in these platform based markets. Specifically, I look at three different platforms including an augmented-reality platform, sponsored search ad platform and a user generated content platform. Each of these platforms have a unique properties that lead to strategic behavior by their users. The design features of the platform impact this behavior leading to newer outcomes. Studying this impact, especially from a policy perspective, will lead to designing stratified interactions between multiple sides of the platforms, as shown in figure 1.1.

In the first essay of my dissertation, I study the economic impact of augmented reality on local businesses. Specifically, we study Pokémon Go, the most popular augmented-reality game, which combines geo-spatial elements with gamification artifacts to incentivize user movement in the physical-world. The game acts as a platform to bring players and businesses together, as shown in figure 1.2. Some businesses in the vicinity of these artifacts

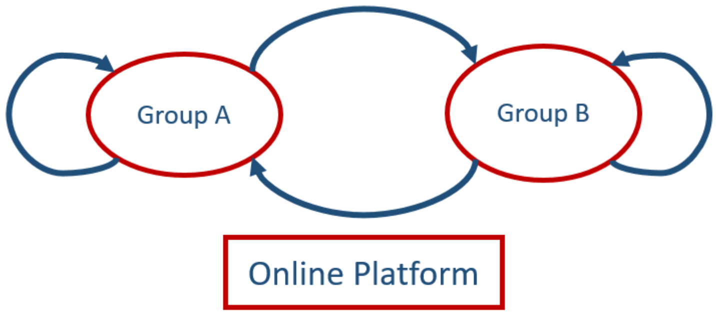


Figure 1.1.: Online Platforms with same-side and cross-side network effects

receive an externality due to user engagement with the game. This study is important because Niantic, the creator of Pokémon Go, is having paid partnerships with businesses like Starbucks to place in-game artifacts at their locations. We take advantage of a natural experiment setting that emerges due to the initial placement of in-game artifacts in Pokémon Go. We rely on online reviews of these businesses to measure the consumer behavior. We also extract various characteristics from the review text using Natural Language Processing (NLP) techniques such as sentiment analysis and topic modeling. Using propensity score matching in conjunction with a difference-in-difference model, we find that businesses near in-game artifacts enjoy higher engagement as well as more positive consumer perception. In addition, we examine the heterogeneity of the effect of in-game artifacts on consumer engagement and perception with respect to restaurant characteristics such as restaurant affordability, popularity, and location. These insights help policymakers to make decisions when designing incentives in such markets. This is the first work to examine the economic impact of augmented reality technology.

The second essay focuses on the design features of sponsored search auction platforms. As automated robots and technology tools become more common, the frictions in these markets are known to be significantly decreasing. We study the impact that reduced frictions have on outcomes of the market. The impact we study is effect of market frictions on strategic interactions between the advertisers as shown in figure 1.3. It is hard to study

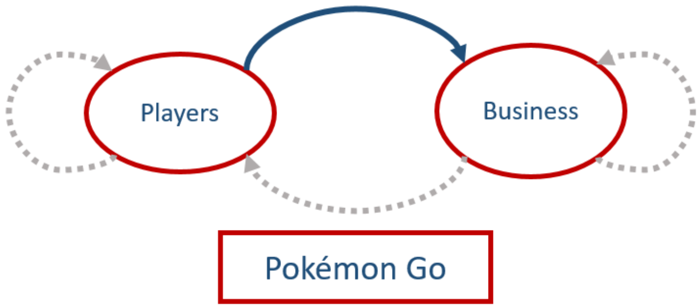


Figure 1.2.: Pokémon Go as a platform

this problem empirically because the participant's valuations are latent and unobserved. Therefore, we study this using a computational approach in conjunction with an experiment. More specifically, we model computational agents using reinforcement learning to derive hypotheses pertaining to the market outcomes in Generalized Second Price (GSP) auction environments, the most popular auction on sponsored search platforms. We further validate these hypotheses in a lab experiment. We find that, as frictions decrease, participants who do not win the auction inflate their bids, thereby causing the winners to pay a higher price. This cascading effect has direct implications for market efficiency as well as the platform. We conclude that frictions in small quantities help achieve higher social welfare. Overall, these results have implications for policymakers and auction platform managers in designing incentives for more efficient auctions in such markets.

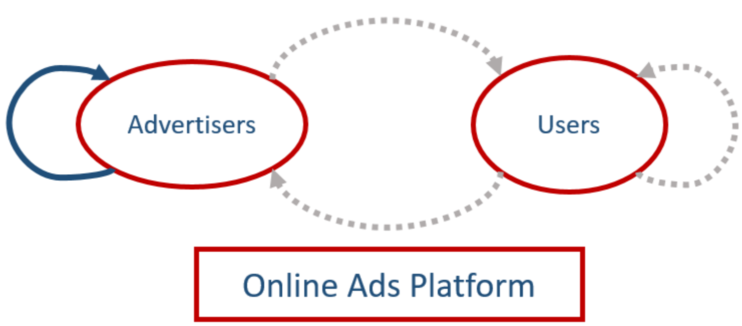


Figure 1.3.: Sponsored search ad auction platform

The third essay focuses on the effects of platform-sponsorship on user generated content platforms. The platform we study has users on one side and businesses on the other. Previous literature has extensively studied the impact of having platform-sponsorships such as status on user contributions. We specifically focus on the impact of losing such status. We study the cross-sided impact of status given to users on the businesses subsequently, as shows in figure 1.4. We utilize user and review data from Yelp.com and focus on the elite status that high-performing reviewers receive. Once their contributions to the platform reduce in volume, elite users lose status. However, as humans are creatures of habit, one may expect that the quality of contributions to not be affected by the loss of status. We utilize NLP to extract various review characteristics including sentiment and topics. Using an empirical strategy, we find that losing status does not modify the topic of the reviews written by the users, on average. This work is currently under progress and I propose to complete the planned analysis for this project by the time of my final defense.

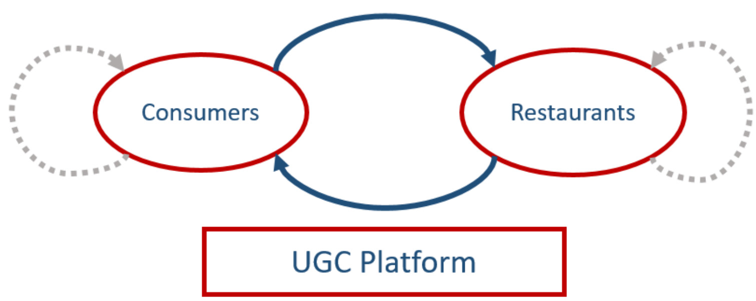


Figure 1.4.: User Generated Content Platform

Overall, this dissertation analyzes three different design problems in the domain of platform-based markets. Specifically, the studies focus on understanding the impact of design artifacts on user behaviour and engagement on these platforms. An updated user behavior leads to trickled down impact of various aspects of the platforms, leading to interesting and important considerations for the policymaker. Two of the chapter in this dissertation focus on user behavior as observed on a user-generated content platform. The other chapter specifically focuses on strategic engagement from the users in an environment with reducing frictions. These studies make a significant contribution towards both academic research as well as industry practice. In the rest of the dissertation is structured as follows. Chapters 2,3, and 4 discuss the first, second, and third essays of my dissertation as described above. Chapter 5 provides a summary of the main findings and establishes a plan of action for the subsequent tasks to accomplish.

2. THE IMPACT OF AN AUGMENTED-REALITY GAME ON LOCAL BUSINESSES: A STUDY OG POKÉMON GO ON RESTAURANTS

2.1 Introduction

Augmented-reality technologies are expected become prominent and important to businesses [Blau et al., 2017]. The convergence of virtual and physical spaces is expected to enable commerce in location-based mixed reality settings to grow to as much as $6.86 billion by 2024 [Grand View Research, 2016]. Not surprisingly, the academic literature has become enthusiastic about this topic with a number of papers studying how this technology affects human behavior [e.g., Billinghurst, 2002]. The focus of our paper is different. We study how the externalities caused by activities in the virtual world impact businesses in the physical world. Specifically, we study the effect of Pokémon Go, currently the most popular augmented-reality application, on local businesses that are associated with the application. To the best of our knowledge, we are one of the firsts to explore the economic implications of augmented-reality technologies.

Pokémon Go is a popular mobile game developed by Niantic Inc. that incorporates the GPS capability and Augmented Reality (AR) technology to locate, capture, battle, and train virtual creatures called Pokémon. Within two months of the game's release on Android and iOS platforms in July 2016, the app generated more than $440 million in revenue from App Store and Google Play Store [Nelson, 2016]. It has become the biggest mobile game in U.S. history [Lovelace Jr, 2016]. The game remains a worldwide phenomenon, even after two years, with 5 million daily active users and a life-time gross revenue of $2.2 billion [Dogtiev, 2018, Pesce, 2018]. The popularity of Pokémon Go is such that retail chains like Starbucks in the United States and McDonald's in Japan have recently started to collaborate with Niantic in a paid partnership and have the in-game virtual artifacts – PokéStop and Gyms[1] – at their retail locations [Liptak, 2016, Olson, 2016]. These partnerships raise a number of interesting and unanswered questions. How much does having a PokéStop and Gym at the location help a business retailer? How should Pokémon Go distribute the locations of these in-game artifacts in a manner that does not devalue the game for the players? How should the sponsorships differ for a retail chain as opposed to an independent business? Of all these questions, in this paper, we study the first. Specifically, we analyze the economic implications of having PokéStops or Gyms at the restaurant locations.

In this research, we leverage a natural experiment setting that emerges due to the initial placement of in-game artifacts in Pokémon Go. During the initial release, these artifacts were placed at several noncommercial locations. Some restaurants happened to be located inside the radius of the artifacts' influence while others were not. These differences are used to identify the treatment effects of in-game artifacts. In the meantime, we rely upon online reviews of these restaurants to measure the change in consumer behavior. Specifically, we use review volume as a proxy for consumer engagement with the restaurant and average star ratings as a proxy for consumer perception toward the restaurant. In addition, we examine the heterogeneity of the effect of in-game artifacts on consumer engagement and perception with respect to restaurant characteristics such as restaurant affordability, popularity, and location. We obtain observational data by collecting locations of the in-game artifacts from the city of Houston, Texas. For restaurant reviews, we use data from one of the major restaurant review platforms in the United States. The same dataset also provides information about characteristics of the restaurants, such as average menu price and location to examine the heterogeneous treatment effect of these in-game artifacts.

[1]PokéStop is an in-game artifact that allows Pokémon Go players to interact by collecting in-game items. Gym is an in-game artifact that allows Pokémon Go players to battle with other Pokémons. Additional details regarding these in-game artifacts are provided in Section 2.3.1

Overall, we find that Pokémon Go has a positive impact on consumer engagement with the restaurants that have PokéStops or Gyms at their location as these restaurants receive a significantly higher number of reviews compared to those without an in-game artifact. By further analyzing the increase in review volume, we find that the presence of an in-game artifact is effective in attracting local consumers while its effect on visiting consumers is minimal. Meanwhile, the presence of an in-game artifact appears to engage new consumers, who never contributed a review before, as well as those who already did. Interestingly, the increase in review volume mostly comes from positive reviewers (i.e., those who tended to write positive reviews in the past). We also find that the average consumer perception of the restaurants located near an in-game artifact improves significantly compared to restaurants that do not. This improvement results from an increase in 4- and 5-star reviews and a decrease in 1-star reviews. As for the moderating effect, the average menu price and the popularity of the restaurant are significant moderators as more expensive and popular restaurants appear to enjoy a lesser benefit in terms of consumer engagement. We also conduct several post-hoc analyses and robustness checks to demonstrate that the characteristics of the reviewers do not fundamentally change during our study period and that the change in behavior we observe can be attributed to the introduction of Pokémon Go. Our research provides insights into the business value of this emerging technology, which could inform the business managers and policymakers about the value of potentially establishing partnership with such an application.

In the next section, we review previous literature related to our study. We then present our research setting and discuss the conceptual framework in Section 2.3. Section 2.4 discusses the data used in this study. In Section 2.5, we describe the econometric model and present the results in Section 2.6. Lastly, we summarize the implications and conclude our research in Section 2.7.

2.2 Literature Review

In this section, we review the prior literature related to our work. Platforms/apps have been quite useful in creating engagements in general and Pokémon Go is one such platform. Therefore, we survey the stream of prior works that have studied how technologies encourage engagement. Recently, there has also been some work focused specifically on Pokémon Go. Given their relevance, such works are reviewed in the second subsection.

2.2.1 A Brief Survey of Platforms That Facilitate Engagement and Mobility

As location-based technologies have gained increasing traction in recent years, so too has the related research. Previous literature has studied the implications of location-based technology in several contexts. For instance, Cho et al. [2011] examined the movement of users in a location-based social network and showed the dependency of periodicity and social relationships on human movement. In addition, Frith [2013] used qualitative interviews to establish that users of location-based social networks tend to change their mobility pattern and enjoy their surroundings more. Also, Frith [2013] explored the gaming elements of a location-based social network and argued that the playful layers of these gaming elements can affect individual behavior in terms of their mobility decision and their experience of the surrounding components. Other works have also confirmed the effect of location-based feature applications on users' mobility choices [Humphreys, 2007, 2010, Licoppe and Inada, 2010]. With such a strong effect on user mobility, Hjorth [2011] proposed that location-based features can combine with a mobile game to create a novel way of experiencing different physical places. Gazzard [2011] reinforced this concept by arguing that location-based mobile games can be supplemented with augmented reality; this has been implemented in Pokémon Go and has become the core element of a user's involvement with and understanding of their surroundings. Concurrently, a limited number of prior works have studied the application of augmented-reality technologies to other industries. For instance, Kaufmann and Schmalstieg

[2003] applied augmented reality to enhance student learning experiences in mathematics and geometry. Beyond these subjects, Antonioli et al. [2014] not only suggested a broader use of augmented reality in education but also highlighted the difficulties of creating such content. Han et al. [2013] interviewed tourists in Dublin and concluded that the use of augmented reality in tourism can generate fruitful results. Except for the papers mentioned in the following subsection, we are not aware of any prior work that studies the business implications of augmented reality in conjunction with other engagement features.

2.2.2 The Impact of Pokémon Go

This subsection presents the literature that specifically studies Pokémon Go and its impact on user behavior. The significant distinction of Pokémon Go from other mobile games, particularly in terms of its influence on users has been recognized in the research community[Nacke et al., 2017]. As a result, it forms a convenient natural experiment framework and has become a platform for researchers in several contexts. In medical research, the focus has centered on the impact of Pokémon Go on the well-being of its players. For example, Howe et al. [2016] use online survey data to show that Pokémon Go players walk 25% more on average after they install the game, although such an increase gradually weakens and ultimately disapperas after five weeks. In addition, Althoff et al. [2016] use enhanced user data from Microsoft Band's physical activity sensors to show empirically that Pokémon Go significantly increases physical activities among users of all ages, genders, weight status, and prior activity levels. The app's ability to reach low-activity populations is particularly unique since they tend not to respond well to apps specifically designed to promote a healthy lifestyle. On the other hand, several studies have reported potential negative consequences of playing Pokémon Go, including Serino et al. [2016] who highlight that the location-based gameplay of the app can drive players into inappropriate areas and increase their risk of abduction or trespassing. In a similar vein, Joseph and Armstrong [2016] argue that the augmented reality feature of the game can cause distraction and increase the risk of being injured while playing the game.

In addition, several studies have been conducted to investigate the design aspect of Pokémon Go and its implications at the macro level. Colley et al. [2017] examine the geography of Pokémon Go using field survey and geostatistical analyses. They show that Pokémon Go amplifies the existing geographically linked biases (e.g., the game favors urban areas more) and that the game influences human mobility patterns on a large scale. Similarly, Sari [2017] uses location data to show the spatial disparities caused by the placement of in-game Pokémon Go artifacts in a French metropolis. In this regard, Adlakha et al. [2017] highlight how important it is for urban planners to design people-space interactions carefully.

Furthermore, research has been done on the adoption of Pokémon Go, the user experience, and the sustainability of the app. Rauschnabel et al. [2017] use a survey of Pokémon Go players to develop a comprehensive framework to explain the benefits and risks of adopting the app. They find that the primary factors that drive players to adopt the game are hedonic, emotional, and social, while physical risks are the primary deterrents. Once adopted, Rasche et al. [2017b] show that the augmented reality feature of the game is critical in retaining active users, that a clear majority of players prefer to play the game alone, and that users tend to play the game continuously. Also, active Pokémon Go players have been shown to have better daily functions and psychosocial functions, which motivates them to spend money on induced consumption, including restaurants and retail stores [Zach and Tussyadiah, 2017]. Lastly, Lalot et al. [2017] conclude that the sustainability of the game depends on its ability to maintain the agreeableness, perseverance, and premeditation of the players. Meanwhile, Rasche et al. [2017a] show that users quit the game because of the lack of challenge and game quality. Niantic has focused on these aspects in their subsequent version releases.

In summary, Pokémon Go has been shown in prior studies to influence its users significantly. This research study extends the extant literature in this area by investigating the *economic* impact of Pokémon Go. To the best of our knowledge, we are the first to offer empirical evidence regarding the impact that Pokémon Go has on local businesses associated with the app.

2.3 Research Context and Conceptual Framework

In this section, we describe the research context and the conceptual framework of our study. Specifically, we describe our empirical setting, including the detail of Pokémon Go in-game artifacts, and discuss the theoretical background for our analysis.

2.3.1 Empirical Setting

In-game Artifacts

Note that the artifact itself is virtual (i.e., it only exists in the game), but each one corresponds to a physical location (i.e., the latitude and longitude in the real world, chosen by Pokémon Go). Players interacting with the artifact have to be present within 40 meters of its real-world location. There are two types of in-game artifacts, "PokéStop" and "Gym." Players who visit a PokéStop can collect in-game items – such as a "PokéBall" (used to capture Pokémons), or a "Potion" (used to heal Pokémons from battle wounds) – that are essential in the game. Since a player is limited to collecting these items only once every 5 minutes, they spend a significant time at PokéStops and visit them often. Players who visit a Gym can use their own Pokémon to fight other Pokémons in the Gym to obtain experience points and in-game currency. The number of Gyms are generally much smaller than the number of PokéStops. Further, since December 2016, Niantic Inc. has flipped the type of in-game artifact (i.e., a PokéStop became a Gym and vice versa) back and forth many times in many locations. For these reasons, we do not differentiate between the artifacts in our analysis

Initial Placement of In-game Artifacts

In a different game called Ingress also developed Niantic Inc. and also an augmented reality game, the players nominated locations for the in-game artifacts (called "Portals"). Niantic considered various factors for those locations – including historical foot traffic and the history or educational value of the place – to decide on the locations of Portals. The Pokémon Go artifacts were simply placed in the same locations as the Portals. When Pokémon Go was released initially, in-game artifacts were only placed at non-commercial locations (such as monuments, churches, libraries). As a result, some businesses happened to be located inside the radius of an in-game artifact while others weren't. We exploit this feature as a natural experiment for identification in our analysis.

2.3.2 Theoretical Backgrounds and Conceptual Framework

Note that, although several types of local businesses (such as shopping malls, restaurants, convenience stores, etc.) may be impacted by Pokémon Go, we specifically chose restaurants as our research context for the following reasons. Firstly, recall that in-game artifacts have limited effective range,[2] which typically cannot cover large business establishments such as shopping malls or grocery stores. Moreover, the size of most restaurants is suitable for our analysis as it is typically within the range of a single in-game artifact. Furthermore, although our dataset contains several types of businesses, the number of restaurants in our dataset far exceeds that of other businesses. Lastly, consumers are generally more connected to restaurants than other retail establishments, especially in terms of expressing their opinions on the product/service quality, thus allowing us to identify the effect of in-game artifacts on consumer engagement and perception – our two dependent variables of interest. Therefore, we hereafter refer to restaurants instead of businesses.

[2] Additional details regarding the in-game artifact are provided in Section 2.3.1

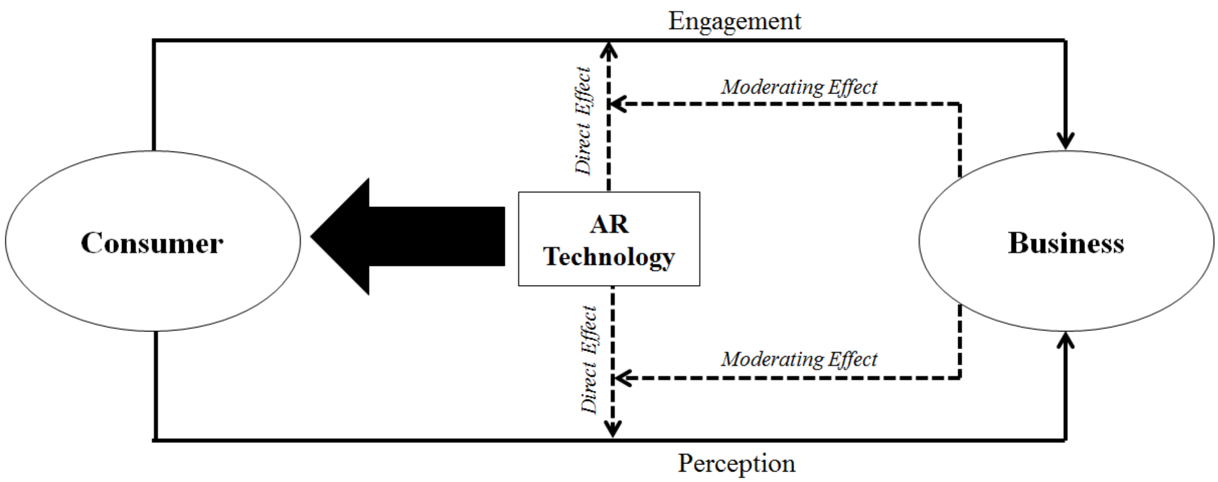


Figure 2.1.: The Overall Framework of This Study

Figure 2.1 summarizes the conceptual framework of our paper. We are interested in how the augmented reality technology in Pokémon Go influences consumer engagement and consumer perception of businesses, along with how these effects are moderated by business characteristics. The first relationship is regarding how in-game artifacts impact the consumer engagement level with the associated restaurants. Generally, consumer engagement is important for the restaurants in the long run [Bowden, 2009] and is a key predictor of the restaurant's performance [Dock et al., 2015]. Such an engagement is expected to be affected by Pokémon Go if the restaurant is within the range of the in-game artifact. Prior research has shown that the physical venues co-located with such virtual artifacts are likely to attract users [e.g., Zach and Tussyadiah, 2017] and also observe the higher degrees of engagement [Gazzard, 2011], We measure consumer engagement with the restaurant by using the number of reviews. Review writing is costly [Burtch et al., 2017], and reviewers need to be substantially engaged to contribute [Ngo-Ye and Sinha, 2014]. Pokémon Go can influence the review writing in one of two ways. One, the game can potentially be a lead for new consumers arriving at the restaurant, some of whom may choose to write the reviews. Two, a consumer who would otherwise not write a review for a restaurant can also become a reviewer because of Pokémon Go's impact. Based on our observational data, it is difficult to distinguish between these two types of effects. However, they tend to share the same direction and result in similar implications (i.e., number of reviews increases).

The second relationship is regarding how the presence of in-game artifacts influences the consumer perception of the restaurant. As Luca (2016) [Luca, 2016] has shown, consumer perception (along with the number of customers) has a significant effect on a restaurant's performance in both the short and long terms. However, once the consumer perception becomes negative and reaches a critical mass, it is difficult to improve their overall perception since that would require them to find additional avenues to create a positive perception among customers. In the context of our study, on the one hand, customers who play Pokémon Go could obtain an additional benefit by interacting with in-game artifacts while visiting a restaurant located near an in-game artifact. If this effect is sufficiently strong, we should expect to see, on average, a positive influence of Pokémon Go on consumer perception. On the other hand, Pokémon Go can also cause undesired behavior [Kari, 2016] and be a potential source of nuisance [Shum and Tranter, 2017]. Potentially, the existence of in-game artifacts can lead to other issues (such as noise, crowding, etc.) that negatively impact consumer perception. Our research empirically identifies the net result of these competing forces to demonstrate the effect of in-game artifacts on consumer perception. We operationalize the measure of consumer perception by observing the change in the average star ratings of the restaurants. Average star ratings are widely used in the literature to capture consumer perception of products and services [Chintagunta et al., 2010, Khern-am nuai et al., 2018b]. Note that we assume there is no fundamental or systematic change in terms of restaurant quality before/after the release of Pokémon Go for the associated restaurants.

Apart from the direct effects of in-game artifacts on consumer engagement and consumer perception, we are also interested in the heterogeneity of these effects. Specifically, we aim to study the moderation effect played by restaurant characteristics. Since food is an experience good, restaurants are vastly heterogeneous in nature. We account for this heterogeneity along the following three dimensions. Firstly, we use the average menu price of the restaurants to measure restaurant affordability. The literature has shown that such a variable influences restaurant performance [Mathe-Soulek et al., 2016], customer satisfaction [Han and Ryu, 2009], and customer behavioral intention [Kwun and Oh, 2004]. Secondly, we use the total number of reviews that each restaurant received before the start of our study period as a proxy for restaurant popularity. The popularity is demonstrated to be a strong moderator in several contexts, including group buying [Zhang et al., 2013] and brand personality [Murase and Bojanic, 2004]. In our context, it would be interesting to investigate whether the effect of in-game artifacts is similar across a spectrum of restaurants of differing popularity. Thirdly, it is possible that, because of augmented reality, the users may be tempted to explore the physical areas near the artifact locations. So, we account for this moderating effect also using area-crowdedness as a measure. For that, we use the total number of restaurants in each zip code and also the total number of in-game artifacts in each zip code as a proxy to measure area crowdedness.

2.4 Data

This research has two primary data sources. The first is the application programming interface (API) of Pokémon Go.[3] This API allows us to collect locations (i.e., lists of latitude and longitude) of Pokémon Go's in-game artifacts reliably. The second data source in one of the most popular online restaurant review platforms in the United States. We collect restaurant information and online reviews from this platform. With regards to the geographical area, the scope of our data is at a city level (i.e., our dataset consists of restaurant reviews and locations of in-game artifacts from one city). We chose Houston as the target city in our research for the following reasons. Firstly, Houston is recognized as one of the most diverse cities in the United States [Gates, 2012]. Therefore, the results obtained from the dataset are less likely to be culturally or ethnically biased. In addition, as our data are from

[3] There are several Pokémon Go API available. In this research, we use pgoapi, which is available at https://github.com/pogodevorg/pgoapi.

restaurant reviews, the multicultural cities typically offer various type of restaurants, thus also minimizing restaurant-type bias. Second, Houston is one of the most populous cities in the United States. As the initial placement of in-game artifacts was based on historical foot traffic, we observe and abundance of in-game artifacts throughout Houston. The availability of these virtual artifacts help us identify their effect on restaurants.

Table 2.1.: Restaurant data collected

ID	Unique identifier of the restaurant
Name	The name of the restaurant
Category	The category of the restaurant (e.g., cafe, bakery)
Address	The address of the restaurant (including zip code)
Average Menu Price	The average menu price of the restaurant
Total Reviews	The total number of reviews received by the restaurant
Average Rating	The total average rating received by the restaurant
Status	The activity status of the restaurant (e.g., open, closed)
Operating times	Hours of operation of the restaurant
Photos & Videos	The number of photos or videos posted for the restaurant

Table 2.2.: Review elements collected

User ID	The unique identifier of review writer
User Name	The name used by the user on the website
Friends	Number of friends that the user has
Reviews	Number of reviews that the user has written
Review Content	Textual content of the review
Star rating	Rating (scale of 1 to 5) that review writer gave to the restaurant
Review date	The date the review was posted
Useful	Number of people who found the review useful
Funny	Number of people who found the review funny
Cool	Number of people who found the review cool

We started to collect the data in December 2016 by using an automated script. We began by acquiring a list of the locations of in-game artifacts established within Houston. There were 4,832 in-game artifacts spread across the city. At the same time, we recorded a list of restaurants located in 88 neighborhoods across the city. We then collected the details of each restaurant, including the restaurant identification, name, average menu price, category, and address of the restaurant. Further, for each restaurant, we also collected online reviews, including the textual content of the review, issued star ratings, date, and reviewer identification. Details of the collected restaurant characteristics and review elements are provided in Tables 2.1 and 2.2. In total, the dataset consists of 3,424 restaurants, of which 327 have an in-game artifact nearby. In terms of time, our dataset consists of all reviews until December 2016 for each restaurant. For our analysis, we consider the reviews between March 2016 and October 2016 (i.e., 4 months before and after the release of Pokémon Go on July 2016). During this period, there are a total of 67,348 reviews written by 17,417 unique reviewers observed across restaurants. Table 2.3 presents the summary statistics of the variables related to the online review elements collected. Note that crime incidents and average weather are control variables used in our analysis and are described in Section 2.5.2.

Table 2.3.: Summary Statistics of the variables of interest

Variable	**Mean**	**Std Dev.**	**Minimum**	**Maximum**
Restaurant-level				
Number of Reviews	74.49	132.31	1.00	2,402.00
Average Star Rating	3.27	1.35	1.00	5.00
Other Restaurants Nearby	2.77	4.37	0.00	35.00
Words Per Review	100.37	38.34	16.50	511.00
Review Rate (per month)	1.79	4.18	0.01	85.19
Crime Incidents (per month)	2.93	2.77	0.00	21.00
Average Weather (per month)	20.63°C	6.24°C	7.00°C	33.00°C
Reviewer-level				
Number of Restaurants	3.26	8.53	1.00	713.00
Average Star Rating	3.65	1.18	1.00	5.00
Words Per Review	91.93	79.35	0.00	1,021.00
Review Rate (per month)	0.27	1.18	0.01	90.00

2.5 Methodology

Using the data described in the previous section, we construct an empirical model. Since our primary objective is to establish the causal inference of an exogenous event (i.e., the introduction of Pokémon Go's in-game artifacts), we face the identification issue of endogeneity. For example, restaurants that are located near an in-game artifact are probably, on average, more active than restaurants that are not. Therefore, we design our research framework as a quasi-experiment by combining the propensity score matching (PSM) and difference-in-differences (DID) techniques to account for potential endogeneity concerns. These techniques are widely used in the literature for this purpose [e.g., Bapna et al., 2018, Xu et al., 2016]. With this framework, our analysis is analogous to a two-group experiment, where the treated group is the restaurants that are located near an in-game artifact while the control group is the restaurants that are similar to those in the treatment group but are not located near an in-game artifact. Note that we will, hereafter, use the terminology of experiments to simplify the writing, whereas the data are in fact observational. By comparing the difference between these two groups and the difference in pretreatment and posttreatment, we will be able to identify causally the impact of Pokémon Go on local restaurants.

2.5.1 Propensity Score Matching

Our first task is to utilize propensity score matching to create a dataset that mimics a randomized experiment research design. Particularly, we use PSM to create a pair of similar restaurants, where one is located near an in-game artifact ("treated") while the other is not ("control"). Using the PSM technique, we compute the probability of each observation receiving the treatment, conditional on the observable characteristics. Since our intention is to identify a pair of restaurants that are similar in terms of observable characteristics before the release of Pokémon Go and that are located near one another, our matching variables in the PSM process are the total number of reviews, average star ratings, review rate (average number of reviews in a day), price range, and location. The matching process is executed by using all the data before the release of Pokémon Go. We discard observations that are lying outside of the common support and finally obtain 654 restaurants in the matched sample, with 327 in each group. To verify that our matching attempt is a success, we then use t-tests to verify the differences of matching variables between each group.

Table 2.4.: Results from t-tests for differences in matching variables

	Treated	Control	t statistic	p-value
Total number of reviews	148.63	137.05	0.7760	0.4380
Average star ratings	3.37	3.38	0.0896	0.9286
Average Menu Price	16.69	16.84	0.1775	0.8591
Review Rate	0.0863	0.0899	0.2996	0.7643

Results in Table 2.4 show that there is no significant difference between the treated group and the control group in terms of matching variables. We also verify the location of the restaurant pair (i.e., the one in the treatment and the one in the control groups) and find that restaurants in every pair are in the same neighborhood.

2.5.2 Difference-in-differences

With the matched dataset, we construct the data into a panel dataset such that each observation corresponds to a restaurant. Meanwhile, the unit of time is defined as semi-monthly. Hence, we have a total of 16 time periods, namely 8 periods before and 8 after the introduction of Pokémon Go. The primary dependent variables of our model are the number of reviews each restaurant receives in each period (which we use as a proxy to measure consumer engagement with the restaurant) and the average star rating of the reviews that each restaurant receives in each period (which we use as a proxy to measure consumer perception of the restaurant).

Parallel Trend Assumption

Next, since we intend to use the difference-in-differences analysis as a main model, we test whether our matched sample satisfies the parallel trend assumption. Essentially, we need to demonstrate that our dependent variables in the treatment and control groups follow the same trend before the treatment start time. Here, we employ the Augmented Dickey-Fuller test of stationarity, an approach used in prior works [e.g., Khern-am nuai et al., 2018b]. Recall that the definition of a stationarity time series is one in which the mean, variance, and autocorrelation structure do not change over time. Hence, if the differences of our dependent variables between the treated and control groups satisfies the test for stationarity (i.e., a test where the null hypothesis is that the variable contains a unit root and the alternative hypothesis is that the variable is generated by a stationary process), then it would indicate that those variables in the treated and control groups follow the same trend.

Table 2.5.: Results of the Augmented Dickey-Fuller Test of Stationarity

	Z(t) from Augmented DickeyFuller test
Total Number of Reviews	-3.362**
Average star ratings	-3.521***

Table 2.5 reports the results from the Augmented Dickey-Fuller test of stationarity. The test for number of reviews and average star ratings both reject the null hypothesis of a unit root, suggesting that the differences of the dependent variables between the two platforms are stationary and the parallel trend assumption holds.

Model Specifications

Now that the parallel trend assumption is verified, we can properly employ the difference-in-difference regression to analyze the impact of Pokémon Go on these restaurants. Our model specification takes the following form:

$$DV_{it} = \gamma(Treatment_i \times After_t) + \boldsymbol{\beta X_{it}} + \alpha_i + \delta_t + \epsilon_{it}. \tag{2.1}$$

In Equation 2.1, subscript i denotes the restaurant, and t denotes the time period (i.e., $t = 1$ for the first time period, $t = 2$ for the second time period, and so on). DV_{it} represents the dependent variable of interest. Meanwhile, α_i captures restaurants fixed effects, which represent the restaurant's specific characteristics that impact our dependent variables and vary across a pair of matched restaurants but remain the same across time. For example, a matched pair of restaurants located downtown could be significantly different from the ones located in the suburbs. δ_t captures time fixed effects, which represent time-specific characteristics that affect our dependent variables. $Treatment_i$ is an indicator variable that represents if the restaurant is treated. $After_t$ is an indicator to represent the post-treatment periods ($t > 8$). Lastly, $\boldsymbol{X_{it}}$ is a vector that represents control variables that vary in both time and location. We collect crime, that is the number of crimes that occurred within 100 meters of each restaurant in each time period, from SpotCrime API.[4] This API provides details about the crime type, its date and time and geolocation. In addition, we collect the average temperature for each restaurant location in each period, from Wunderground.com, a weather information website.[5]

Apart from the effect that in-game artifacts may have on nearby restaurants, we are also interested in the characteristics of the heterogeneous treatment effect. Particularly, we examine how the affordability, popularity, and location of the restaurant moderates the effect that in-game artifacts have on consumer engagement and consumer perception. We calculate the average menu price based on information provided on the review platform as a proxy for restaurant affordability. In the meantime, the total number of reviews for each restaurant before the study period is used as a proxy for restaurant popularity. Lastly, we calculate the total number of restaurants and the total number of in-game artifacts in a given zip code and use them as proxies for the crowdedness of restaurant location. We include these variable,

[4]SpotCrime is a public facing crime map and crime alert service, which helps users check crime occurrences across the United States.

[5]A commercial weather service providing real-time weather information.

$Moderator$, as an interaction term that moderates the effect of $Treatment_i \times After_t$ in our specification. Formally, our second model specification is:

$$\begin{aligned} DV_{it} &= \gamma(Treatment_i \times After_t) + \boldsymbol{\beta X_{it}} + \theta Moderator_i \\ &+ \eta(Treatment_i \times After_t \times Moderator_i) + \alpha_i + \delta_t + \epsilon_{it}. \end{aligned} \tag{2.2}$$

2.6 Empirical Results

This section reports the results from our empirical analyses. Note that, for the sake of brevity, we denote $Treatment_i \times After_t$ with the term $ArtifactInfluence$ when reporting the results. Hence, $ArtifactInfluence$ is a dummy variable that takes the value of 1 if the restaurant is treated (i.e., located near an in-game artifact) in the posttreatment period (i.e., after Pokémon Go was released or $t > 8$), and 0 otherwise.

2.6.1 The Effect of In-game Artifacts on Consumer Engagement

We first examine the effect of in-game artifacts on consumer engagement by using the difference-in-differences regression in Equation 2.1 on the number of reviews. Note that the number of reviews per restaurant, which is our dependent variable, follows the power law distribution. Therefore, we apply a natural logarithm transformation to it.[6] Table 2.6 reports the regression results.

We find that after Pokémon Go was released, restaurants in the radius of an in-game artifact obtain a significant increase in consumer engagement in terms of the number of reviews the restaurant attains (Column 1). More specifically, these restaurants an increase 5.7% in the number of reviews. This result is not surprising since anecdotal evidence suggests that the presence of in-game artifacts drives foot traffic to the location [e.g., Morrison, 2016]. Next, we expand on this finding by investigating the dynamic behind the increase in

[6]Since the number of reviews per restaurant can be 0, we use log (1+number of reviews).

Table 2.6.: The effect of an in-game artifact on consumer engagement

	log(number of reviews)
ArtifactInfluence	0.057*** (0.016)
Weather	0.038** (0.017)
Crime	0.002 (0.002)
Constant	-0.235 (0.344)
Restaurants Fixed Effect	Yes
Time Fixed Effect	Yes
R-squared	0.41
N	10464

Note: Standard errors in parentheses are robust and clustered by restaurant. * $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

consumer engagement. Particularly, we examine the change in the composition of reviewers who contribute reviews to the restaurants in our study periods.

Firstly, we examine whether the increase of review volume that we observe comes from local reviewers or visitors. We separate the reviews in to two categories based on the location of the reviewer. The location of the reviewer is determined through the reviewer's self-reported location, as provided by the platform. If the location reported is in Texas, we mark the reviewer as an in-state reviewer and all other reviewers are marked as out-of-state. We present the results of this analysis in Table 2.7. Interestingly, the results show that the increase in review volume comes mostly from local reviewers. Meanwhile, although the effect of in-game artifacts on consumer engagement of out-of-state reviewers is positive, the size of such an effect is quite negligible. In other words, the impact of the presence of in-game artifact on consumer engagement appears to be more prevalent amongst locals. This difference may be attributed to the fact that local Pokémon Go players are likely to explore their localities due to easier access, as compared to the visitors.

Secondly, we investigate whether the increase in the number of reviews is owed to new reviewers or existing ones. We separate the data into two groups based on the previous activities of the reviewer. Reviewers who never wrote reviews before the release of Pokémon Go are classified into the new reviewer group. Meanwhile, reviewers who wrote at least

Table 2.7.: The effect of an in-game artifact on consumer engagement, with respect to reviewers' home location

	log(number of reviews)	
	in-state	out-of-state
ArtifactInfluence	0.051*** (0.015)	0.006 (0.009)
Weather	0.032** (0.016)	0.009 (0.009)
Crime	0.002 (0.002)	0.001 (0.001)
Constant	-0.202 (0.333)	-0.043 (0.185)
Restaurants Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
R-squared	0.23	0.39
N	10464	10464

Note: Standard errors in parentheses are robust and clustered by restaurant. * $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

one review before Pokémon Go was released are considered existing reviewers. We report the results of this analysis in Table 2.8. We observe that the in-game artifacts work well in stimulating consumer engagement among both the new reviewers and existing reviewers. Note that we also perform an alternative specification by separating the reviewers into active and inactive reviewers using the median of the review volume per user. The results are qualitatively similar to the results observed here.

Table 2.8.: The effect of an in-game artifact on consumer engagement, with respect to reviewers' previous review volume

	log(number of reviews)	
	new reviewers	existing reviewers
ArtifactInfluence	0.029*** (0.009)	0.043*** (0.015)
Weather	-0.020** (0.009)	0.050*** (0.016)
Crime	0.003** (0.001)	-0.000 (0.002)
Constant	0.370* (0.189)	-0.471 (0.332)
Restaurants Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
R-squared	0.28	0.40
N	10464	10464

Note: Standard errors in parentheses are robust and clustered by restaurant. * $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

Thirdly, we analyze whether the increase in the review volume comes from negative reviewers (i.e., reviewers who usually post negative reviews) or positive reviewers (i.e., reviewers who usually post positive reviews). We consider the mode of reviews made by each reviewer before the release of Pokémon Go as a separator. Reviewers with a mode less than or equal to 3 are considered negative reviewers, while the others are considered positive reviewers. According to the results in Table 2.9, the increase in the review volume that we observe in the main results comes from positive reviewers. Meanwhile, the coefficient of the effect of an in-game artifact on the number of reviews is negative for negative reviewers, though the effect is statistically insignificant. In other words, the in-game artifacts appear to be effective in eliciting more reviews from positive reviewers. We will explore more the dynamic of the effect of in-game artifacts on review valence further when we investigate the effect of in-game artifacts on consumer perception in the next section.

Table 2.9.: The effect of an in-game artifact on consumer engagement, with respect to reviewers' previous review valence

	log(number of reviews)	
	negative reviewers	positive reviewers
ArtifactInfluence	-0.015 (0.010)	0.071*** (0.015)
Weather	0.008 (0.010)	0.038** (0.016)
Crime	-0.000 (0.002)	0.002 (0.002)
Constant	-0.075 (0.219)	-0.270 (0.332)
Restaurants Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
R-squared	0.19	0.39
N	10464	10464

Note: Standard errors in parentheses are robust and clustered by restaurant. * $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

In summary, our first main result demonstrates that restaurants that are located inside the radius of an in-game artifact in Pokémon Go received a significantly higher amount of reviews after Pokémon Go was introduced, suggesting that the effect of in-game artifacts on consumer engagement is positive and significant. Our subsequent analyses to identify the mechanic behind this increase reveals that the increase in the review volume mostly originates from local users who usually posted positive reviews in the past. Nevertheless, it is interesting to note that Pokémon Go appears to be significantly effective in stimulating consumer engagement for both new and current users.

2.6.2 The Effect of In-game Artifacts on Consumer Perception

In this subsection, we again use the difference-in-differences regression specified in Equation 2.1 to investigate the effect of in-game artifacts on consumer perception. As previously mentioned, the dependent variable for this analysis is the average star rating of each restaurant. Table 2.10 reports the regression results.

Table 2.10.: The effect of an in-game artifact on consumer perception

	average star ratings
ArtifactInfluence	0.273*** (0.048)
Weather	0.060 (0.058)
Crime	0.008 (0.007)
Constant	2.828*** (1.189)
Restaurants Fixed Effect	Yes
Time Fixed Effect	Yes
R-squared	0.34
N	5631

Note: Standard errors in parentheses are robust and clustered by restaurant. * $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

We find that, after the release date of Pokémon Go, consumer perception of restaurants near an in-game artifact is, on average, significantly more positive in comparison with restaurants that do not have in-game artifacts nearby. To investigate further, we analyze the change in review volume based on the star ratings issued, which provide the better understanding of the increase in the average star ratings we observe. Particularly, we separate the reviews into 5 groups based on the star rating associated with it and analyze the change in review volume associated in each group. Results from this analysis are reported in Table 2.11.

Table 2.11.: The effect of an in-game artifact on consumer perception, separating by the star issued

	log(number of 5-star reviews)	**log(number of 4-star reviews)**	**log(number of 3-star reviews)**	**log(number of 2-star reviews)**	**log(number of 1-star reviews)**
ArtifactInfluence	0.034**	0.050***	-0.004	-0.003	-0.018**
	(0.014)	(0.012)	(0.009)	(0.007)	(0.008)
Weather	0.015	0.026**	-0.004	0.008	-0.004
	(0.014)	(0.013)	(0.009)	(0.008)	(0.008)
Crime	0.001	0.002	0.000	0.003***	-0.003**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Constant	-0.114	-0.348	0.234	-0.158	0.086
	(0.298)	(0.263)	(0.196)	(0.161)	(0.175)
Restaurantsr Fixed Effect	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
R-squared	0.24	0.21	0.19	0.14	0.17
N	10464	10464	10464	10464	10464

Note: Standard errors in parentheses are robust and clustered by restaurant.
* $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

The results in Table 2.11 reveal that the increase in the average star rating among restaurants located near an in-game artifact after the release of Pokémon Go can be attributed to the significant increase in the volume with 4- and 5-stars reviews, and the significant decrease in the volume of 1-star reviews. Meanwhile, the volume of reviews with moderate ratings (i.e., 2 and 3 stars) remain essentially unchanged. These results carry two interesting implications. Firstly, although our results regarding the effect of in-game artifacts on consumer engagement demonstrate that the in-game artifact is significantly effective in attracting new reviewers to contribute, it does not alleviate the issue of review extremity bias as demonstrated in Hu et al. [2009]. On the other hand, the bias appears to shift from bimodal to unimodal since there is a significant increase in positive reviews and an equally noteworthy decrease in negative reviews. Thus, although this type of external event may appear to positive for the businesses involved, it also poses a challenge to the review platform to handle the issue of reporting bias. Secondly, if the introduction of in-game artifacts is significantly effective in engaging positive reviewers while its effect on negative reviewers is statistically insignificant, it turns out that the increase in positive reviews is significant and the decrease in negative reviews is also significant. In other words, although negative reviewers might not write reviews less often, the overall negative reviews actually decrease.

Overall, we find that the presence of an in-game artifact significantly affects nearby restaurants after Pokémon Go was released in terms of the consumer perception. Restaurants that have an in-game artifact nearby experience better consumer perception than those located outside the radius of an in-game artifact while such an enhancement comes from the significantly higher number of extremely positive reviews (i.e., 4- and 5- star reviews) and the significantly lower number of extremely negative reviews (i.e., 1-star reviews).

2.6.3 The Moderating Effect of Business Characteristics

To further our understanding of the effect that an in-game artifact has on nearby restaurants, in this subsection, we investigate whether these effects are moderated by the characteristics of the restaurants in our study.

Business Affordability

We first examine the moderating effect of the restaurant's affordability in our study. We use the average menu price indicated by the review platform as a moderator and use the difference-in-differences regression framework to analyze the data according to Equation 2.2. Note that the average menu price is not available for a few restaurants on the review platform, which consists of about 1.5% of the dataset, so we drop such observations from the analysis. The results of this analysis are reported in Table 2.12. We find that after adding the *AverageMenuPrice* as an interaction term, the main effect of *ArtifactInfluence* on the number of reviews and average star ratings remains statistically significant. In addition, the interaction term itself is negative and statistically significant for the number of reviews while the interaction term is negligible and not statistically significant for average star ratings. This finding suggests that the effect of in-game artifacts on consumer engagement is particularly strong for inexpensive restaurants but the effect begins to fade for restaurants with an average menu price of $45. In other words, inexpensive restaurants enjoy the benefit of having an in-game artifact nearby after the release of Pokémon Go more than their expensive counterparts. In the meantime, the effect of in-game artifacts on consumer engagement appears to be homogeneous among restaurants with different average menu prices.

Table 2.12.: Restaurant heterogeneous effect - based on average menu price

	log(number of reviews)	average star ratings
ArtifactInfluence	0.091*** (0.025)	0.271*** (0.082)
ArtifactInfluence × *AverageMenuPrice*	-0.002** (0.001)	0.000 (0.004)
AverageMenuPrice	0.011*** (0.001)	0.006** (0.002)
Crime	0.004 (0.002)	0.009 (0.007)
Weather	0.038** (0.017)	0.049 (0.057)
Constant	-0.325 (0.346)	3.005** (1.185)
Restaurants Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
R-squared	0.42	0.34
N	10304	5618

Note: Standard errors in parentheses are robust and clustered by restaurant.
* $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

With this finding, the natural follow-up question is why cheaper restaurants manage to obtain better consumer engagement. One of the explanations is that consumers of expensive restaurants could crowd-out as Pokémon Go-induced consumers may be more of a nuisance than ordinary consumers. Morever, the results from Section 2.6.1 demonstrate that Pokémon Go is significantly effective in bringing in new reviewers; it is possible that these new reviewers prefer cheaper restaurants (since the benefit of in-game artifacts remains the same regardless of the location). In this regard, we attempt to capture the preference of consumers in terms of business affordability by calculating the percentage of the number of reviews written by new vs. active reviewers for restaurants with different price ranges. With this proxy, we assume that consumers who write more reviewers for cheap restaurants prefer cheap restaurants and vice versa. Results in Table 2.13 indicate that new reviewers prefer low-priced restaurants than active reviewers. As a result, cheaper restaurants enjoy more consumer engagement after Pokémon Go was released than more expensive restaurants.

Table 2.13.: T-tests for differences in price-ranges between new and active reviewers

	New Reviewers	Active Reviewers	t statistic	p-value
$	0.393	0.274	4.749	0.098
$$	0.584	0.642	-7.121	0.000
$$$	0.023	0.078	-2.339	0.240
$$$$	0.0	0.005	-4.916	0.000

Business Popularity

In this subsection, we analyze the impact of the in-game artifact as moderated by the popularity of the restaurant. We define restaurant popularity by using the total number of reviews written for each restaurant before the beginning of our study period ("*Total-Reviews*") as a proxy. We still rely on the difference-in-differences regression framework specified in Equation 2.2 and interact *TotalReviews* with *ArtifactInfluence*. We find that the main effect of in-game artifacts on consumer engagement and consumer perception remain the same. Meanwhile, the moderating effect of restaurant popularity is statistically significant for consumer engagement. Interestingly, the coefficient of *ArtifactInfluence X TotalReviews* is negative, suggesting that the increase in consumer engagement due to in-game artifacts is higher for less popular restaurants. Particularly, the effect begins to diminish for restaurants with 533 reviews before Pokémon Go was released. This result can be explained by considering the search cost of restaurant patrons. Arguably, the search cost of more popular restaurants would be lower than that their of less popular counterparts. However, in-game artifacts would reduce the search cost to be at the same level for all the restaurants because the benefit of interacting with the artifacts is uniform regardless of the location. In this regard, less popular restaurants would enjoy a greater reduction in search cost and would hence benefit in terms of an increase in consumer engagement. Meanwhile, the moderating effect of restaurant popularity on consumer perception is statistically insignificant, suggesting that the effect of in-game artifacts on consumer perception is not significantly among between restaurant with different degrees of popularity.

Table 2.14.: Restaurant heterogeneous effect - based on restaurant popularity

	log(number of reviews)	average star ratings
ArtifactInfluence	0.0533*** (0.0160)	0.2106*** (0.0583)
ArtifactInfluence × *TotalReviews*	-0.0001** (0.0001)	0.0002 (0.0001)
TotalReviews	0.0023*** (0.0000)	0.0016*** (0.0001)
Crime	-0.0002 (0.0021)	0.0081 (0.0068)
Weather	0.0149 (0.0145)	0.0276 (0.0566)
Constant	0.1015 (0.3013)	3.4046*** (1.1701)
Restaurants Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
R-squared	0.54	0.36
N	10464	5631

Note: Standard errors in parentheses are robust and clustered by restaurant.
* $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

Business Location

Next, we examine whether the effect of in-game artifacts on consumer engagement and consumer perception is different based on the location of the restaurants. Particularly, the moderating variables of interest are the total number of restaurants in a particular zip code, and the total number of Pokéstops and Gyms in a particular zip code, both of which are a proxy for the crowdedness of the given zip code. For example, downtown businesses tends to have more traffics than those in a suburb. We interact these moderating variables with *ArtifactInfluence* and use the regression framework specified in Equation 2.2. The results of the moderating effect of the total number of restaurants in each zip code is reported in Table 2.15. Meanwhile, the results of the moderating effect of the total number of Pokéstops and Gyms are reported in Table 2.16. The results are consistent for both definitions of area crowdedness. Namely, the main effect of in-game artifacts on consumer engagement and consumer perception is positive and statistically significant. However, the interaction term (i.e., *ArtifactInfluence* $\times$ *NumRestaurants* and *ArtifactInfluence* $\times$ *NumArtifacts*) is statistically insignificant, suggesting that the effect of in-game artifacts on consumer engagement and consumer perception is not significantly different for restaurants located in areas with different degrees of crowdedness.

Table 2.15.: Restaurant heterogeneous effect - based on area crowdedness (number of restaurants in a zip code)

	log(number of reviews)	average star ratings
ArtifactInfluence	0.080*** (0.028)	0.391*** (0.088)
ArtifactInfluence $\times$ *NumRestaurants*	-0.000 (0.000)	-0.001 (0.001)
NumRestaurants	0.008 (0.013)	0.010 (0.046)
Crime	0.002 (0.002)	0.008 (0.007)
Weather	0.037** (0.017)	0.055 (0.058)
Constant	-0.258 (0.353)	2.886** (1.224)
Restaurants Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
R-squared	0.41	0.34
N	10464	5631

Note: Standard errors in parentheses are robust and clustered by restaurant.
* $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

Table 2.16.: Restaurant heterogeneous effect - based on area crowdedness (number of Pokéstops and Gyms in a zip code)

	log(number of reviews)	average star ratings
ArtifactInfluence	0.041** (0.021)	0.264*** (0.060)
ArtifactInfluence $\times$ *NumArtifacts*	0.000 (0.000)	0.000 (0.001)
NumArtifacts	-0.002*** (0.000)	-0.002* (0.001)
Crime	0.003 (0.002)	0.008 (0.007)
Weather	0.044*** (0.017)	0.069 (0.058)
Constant	-0.303 (0.344)	2.732** (1.194)
Restaurants Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
R-squared	0.41	0.34
N	10464	5631

Note: Standard errors in parentheses are robust and clustered by restaurant.
* $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

In summary, we find the effect of in-game artifacts on consumer perception to be homogeneous. The effect is positive and significant for all of the specifications with all of our moderators but the coefficient of the interaction terms is not statistically significant. In other words, restaurants that are located near an in-game artifact enjoy a better consumer perception regardless of their characteristics, such as the affordability, popularity, and location. In the meantime, these characteristics appear to significantly moderate the effect that in-game artifacts have on consumer engagement. Particularly, such an effect is weaker for both more expensive and popular restaurants. However, the crowdedness of the area that the restaurants are located does not appear to be moderating the effect of in-game artifacts on consumer engagement.

2.6.4 Post-hoc Analysis

So far, we empirically demonstrate the effect of in-game artifacts on consumer engagement and perception, along with the moderating effect of business characteristics. In this section, we provide two additional analyses that are relevant to our main analysis: the potential spill-over effect from Pokémon Go-related promotion and the change in consumers' review-generating behavior after the release of Pokémon Go.

Potential Spill-over Effects from Pokémon Go-related Promotion

The first extension is to address the concern that the effect we observe might be a *secondary* one of Pokémon Go and not directly from the game itself. For example, there are several news reports regarding restaurants that offer Pokémon Go related promotions to attract customers that are Pokémon Go players [e.g., Brown, 2018]. In this regard, it is plausible that restaurants that are located near an in-game artifact may offer special promotions to Pokémon Go players, which also affect their engagement and perception. This issue is particularly important because this confounding factor cannot be removed from the difference-in-differences analysis. To alleviate this concern, we conduct two sets of analyses.

Firstly, we observe that restaurants that offering Pokémon Go related promotions tend to capture media attention, as witnessed with a bar & grill in Bremerton, WA [Zhu, 2016], a pizza bar in Queens, NY [Sidahmed, 2016], and a sandwich shop in Charleston, SC [Perkins, 2016]. Therefore, it is reasonable to assume that this type of offer would appear in a Google search trend of the restaurant's name (e.g., the name of the restaurant plus "Pokémon Go promotion"). For this reason, we develop a programming script to obtain the Google search trend of each treated restaurant in our dataset. However, we find no significant search interest for any of the treated restaurants during the timeframe of our study. Hence, it is safe to assume that any Pokémon Go-related promotions, were not of a significant magnitude in terms of attracting customers.

Secondly, to alleviate the concern further, we take advantage of the discussion in the reviews posted in our dataset. It is well recognized that online reviews tend to include information related to special offers and promotions [e.g., Li, 2016]. In this regard, we test the change in the amount of promotion-related keywords in the reviews of restaurants with/without an in-game artifact before/after Pokémon Go was released. If a significant portion of the restaurants located near an in-game artifact in our dataset offers a Pokémon Go promotion, we would expect to observe a positive and significant coefficient of *Artifact-Influence* here. According to the results in Table 2.17, we do not have evidence that such a promotion exists.

The Change in Consumer Behavior

In this section, we shift our focus to the changes in consumer behavior after Pokémon Go was released. Particularly, we conduct our analyses through the lens of online to observe the changes in user review-writing behavior during our study period, both in terms of the textual content and characteristics of the reviews.

Review Content (Pokémon Go vs. Restaurant)

Table 2.17.: The effect of an in-game artifact on promotion related reviews

	promotion-related keywords
ArtifactInfluence	0.004 (0.008)
Crime	-0.001 (0.001)
Weather	0.017*** (0.006)
Constant	-0.341*** (0.120)
Restaurants Fixed Effect	Yes
Time Fixed Effect	Yes
R-squared	0.10
N	10464

Note: Standard errors in parentheses are robust and clustered by restaurant. * $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

Firstly, we investigate the presence of Pokémon Go-related discussions in the post-treatment reviews. Although our main analyses demonstrate that restaurants located near an in-game artifact receive a higher number of reviews that are also more positive, one could argue that such an increase may not be directly attributed to consumer engagement and perception because the nature of the reviews changes from reviewing the restaurant experience (i.e., organic reviews) to reviewing the Pokémon Go experience at restaurant site (i.e., inorganic reviews). To investigate whether the introduction of Pokémon Go changes the nature of reviews for treated restaurants, we create an exhaustive list of words from a glossary on the Pokémon Go website, including all the names of Pokémon, relevant items, characters, etc. After excluding common words that normally appear in English dictionaries, we extracted 549 words that are specific to Pokémon Go. Following that, we filter the reviews of the treated restaurant after the release of Pokémon Go using the list of keywords we developed and find that only 11 reviews from 7 restaurants contain one or more words in the list, which constitutes about 0.3% of the post-treatment reviews. We run the regression analyses again by excluding these reviews and the results are qualitatively the same as our main results.

Change in Review Topics

Table 2.18.: The effect of in-game artifacts on Topics

	topic 1	topic 2	topic 3	topic 4	topic 5
ArtifactInfluence	0.007	-0.006	0.001	0.004	-0.006
	(0.011)	(0.011)	(0.006)	(0.010)	(0.006)
Crime	0.001	0.002	-0.002**	0.000	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Weather	-0.026**	0.003	-0.020***	0.028***	0.011*
	(0.010)	(0.010)	(0.005)	(0.009)	(0.006)
Constant	0.790***	0.226	0.423***	-0.316	-0.116
	(0.215)	(0.205)	(0.112)	(0.193)	(0.119)
Restaurants Fixed Effect	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
R-squared	0.18	0.15	0.44	0.26	0.35
N	5622	5622	5622	5622	5622

Note: Standard errors in parentheses are robust and clustered by restaurant.
* $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

Secondly, we perform topic modeling to analyze the changes in the type of topics discussed in the post-treatment period. We develop the topics using the Latent Dirichlet Allocation (LDA) algorithm to determine the topic weights for each review in the treatment group. Here, we specify the number of topics as 5 by using a heuristic approach, which compares the decrease in sum square errors with respect to the increase in topics. Previous literature has shown that the results based on this criterion is not significantly different from those of more complicated criteria [e.g., Kodinariya and Makwana, 2013]. To evaluate any changes in the topic weight distribution after the release of Pokémon Go, we estimate the model in Equation 2.1. The results are reported in Table 2.18. We find that the weights on none of the topics change significantly. This suggests that the reviews may not be affected by the presence of an in-game artifact. The reviewers continue to talk about similar topics as before. Note that we have N=5622 observations here, while N=5631 in Table 2.10. This is because some reviews were not written in English (e.g., they are purely in emoticon), and were excluded while calculating topic weights and review characteristics.

Change in Review Characteristics

Finally, we also consider other review-related metrics to examine whether they change post treatment since the change in one topic distribution may or may not affect the overall review characteristics. To examine if such a change occurs, we consider four standard measures: i) review length, which is calculated based on the number of characters in a review; ii) Flesch-Kincaid reading ease, which indicates how difficult a statement in English is to understand (a higher score means it is easier to understand); iii) Gunning-Fog index, which estimates of the years of formal education needed to understand the text; and iv) Dale-Chall readability score, which provides a numeric gauge of the comprehension difficulty of the text. Table 2.19 reports the results of the analysis based on the specification described in Equation 2.1 on the four aforementioned variables that capture review characteristics. Overall, we do not find evidence that the review characteristics are affected by the presence of an in-game artifact. Particularly, the length of the reviews, which is typically used as a proxy to measure reviewers' motivation [e.g., Khern-am nuai et al., 2018b], and the readability of the reviews (based on 3 different measures) remain similar both before and after the release of Pokémon Go.

Table 2.19.: Treatment effect on review characteristics

	review length	Flesch-Kincai score	Gunning-Fog index	Dale-Chall score
ArtifactInfluence	2.48	0.11	-0.01	0.00
	(3.54)	(0.36)	(0.10)	(0.04)
Crime	0.26	-0.08	0.03*	0.00
	(0.51)	(0.05)	(0.01)	(0.01)
Weather	1.74	-0.28	-0.09	0.00
	(4.27)	(0.43)	(0.12)	(0.04)
Constant	59.06	92.21***	13.83***	6.18***
	(88.29)	(8.89)	(2.54)	(0.92)
Restaurants Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
R-squared	0.10	0.11	0.10	0.12
N	5622	5622	5622	5622

Note: Standard errors in parentheses are robust and clustered by restaurant.
* $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

In summary, three sets of analyses in this subsection provide further evidence for the underlying mechanism at play in our study. The reviewers do not demonstrate any fundamental changes in their review-writing behavior. They do not specifically discuss Pokémon Go in their review, the topics of discussion remain virtually the same, and the length and readability of reviews, on average, also remain consistent. This suggests that the type of customers who participate are not fundamentally changing, but their overall engagement is significantly higher and their perception is more positive.

2.6.5 Robustness Checks

In this section, we perform several sets of robustness checks based on alternative specifications/approaches to ensure that our results are robust.

Controlling for Immediate Treatment Effects

One may argue that the effect of the game, which received extensive media coverage upon its release, might influence the reviews for the restaurants only around the time of the release and may not remain significant after the initial hype. To ensure that we were not measuring only the immediate treatment effect, we dropped the observation between 16 June 2016 and 15 July 2016 (which is one time period before/after the release of Pokémon Go) and compared 7 time periods before and after the release of Pokémon Go instead. The results based on the specification in Equation 2.1 are reported in Table 2.20. After removing the initial days from the data, the effect of having an in-game artifact nearby is similar to our main results. Restaurants located near an in-game artifact enjoy a higher level of consumer engagement and perception. Interestingly, we also find that the magnitude of the coefficient of *ArtifactInfluence* in this specification is larger than that in the main results, suggesting that the influence of the in-game artifacts is stronger after the initial days of hype.

Additional Matching Variables

Recall that the variables we used for matching were the total number of reviews, average star ratings, review rate, price range of the restaurant, and location of the restaurant.

Table 2.20.: Controlling for immediate treatment effects of Pokémon Go release

	log(number of reviews)	average star ratings
ArtifactInfluence	0.064*** (0.017)	0.290*** (0.052)
Crime	0.003 (0.002)	0.008 (0.007)
Weather	0.034** (0.018)	0.045 (0.062)
Constant	-0.185 (0.366)	3.220**(1.283)
Restaurants Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
R-squared	0.41	0.33
N	9156	4924

Note: Standard errors in parentheses are robust and clustered by restaurant. * $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

However, it is possible that the restaurant category could be significantly important in determining the similarity of restaurants. Therefore, we perform a robustness test by adding restaurant category as an additional matching variable in the process. Recall that the review platform in our study provides multiple categories for each restaurant. For example, a restaurant called Cafe Ginger is listed under the 'Chinese,' 'Sushi Bars,' and 'Seafood' categories. In total, there were 279 such categories in our data. Therefore, to capture the restaurant categories, we use the Principal Component Analysis (PCA) and perform unsupervised dimensionality reduction. PCA maps the data to lower dimensions while representing the variance observed in the data. By only considering components that have at least a 2% explained variance ratio, we obtain 14 principal component variables, which are used as a proxy for restaurant categories while matching. We further include the number of other restaurants in a 100-meter radius as an additional matching variable, to control for competition. We use the geo-locations of the restaurants to calculate this variable. Table 2.21 demonstrates that the matching is a success while Table 2.22 reports our findings from the new matched data. The outcomes are consistent with our main results.

Alternative Matching Algorithm

In this subsection, we consider an alternate matching algorithm to ensure that our results are not driven by the matching algorithm used. Here, we consider an alternative matching

Table 2.21.: Results from t-tests for differences in matching variables

	Treated	Control	t statistic	p-value
Total number of reviews	148.63	142.28	0.4010	0.6885
Average star ratings	3.37	3.29	0.9165	0.3597
Average Menu Price	16.69	16.33	0.4383	0.6612
Review Rate	0.0863	0.0863	0.0049	0.996
Neighboring restaurants	2.74	2.71	0.1811	0.8564

Table 2.22.: Results with additional matching variables

	log(number of reviews)	average star ratings
ArtifactInfluence	0.062*** (0.016)	0.299*** (0.048)
Crime	0.006** (0.002)	-0.009 (0.007)
Weather	0.021* (0.012)	0.053 (0.042)
Constant	0.118 (0.266)	2.820*** (0.920)
Restaurants Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
R-squared	0.416	0.375
N	10464	5574

Note: Standard errors in parentheses are robust and clustered by restaurant.
* $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

algorithm called Coarsened Exact Matching (CEM) [Iacus et al., 2012], which is a non-parametric matching method. CEM creates stratas(clusters) of similar units from both the treatment and control groups. If a treated restaurant has any control group restaurants in the same stratum, they are matched. There may be strata with multiple treatment and control group items, and hence the matching need not be one-to-one. However, we adhere to one-to-one matching to ensure consistency with PSM matching. We also use the same matching variables described in Section 2.5.1. Table 2.23 demonstrates that the treated and control groups are not significantly different after matching. Meanwhile, Table 2.24 presents the regression results for the specification described in Equation 2.1. Observe that CEM yields results that are consistent with our main results since the coefficient of *ArtifactInfluence* is positive and statistically significant for both log(number of reviews) and average star ratings, indicating that the restaurantslocated near an in-game artifact enjoy a higher level of consumer engagement and consumer perception.

Table 2.23.: Results from t-tests for differences in matching variables

	Treated	Control	t statistic	p-value
Total number of reviews	129.51	120.81	0.7131	0.4760
Average star ratings	3.35	3.35	0.0108	0.9913
Average Menu Price	16.09	16.09	0.0	1.0
Review Rate	0.0789	0.0756	0.2991	0.7649

Table 2.24.: Results using Coarsened Exact Matching (CEM)

	log(number of reviews)	average star rating
ArtifactInfluence	0.047*** (0.014)	0.172*** (0.048)
Weather	-0.004 (0.009)	-0.035 (0.033)
Crime	0.001 (0.002)	-0.004 (0.006)
Constant	0.183 (0.190)	1.715** (0.773)
Restaurant-strata Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
R-squared	0.46	0.28
N	10048	5244

Note: Standard errors in parentheses are robust and clustered by restaurant.
* $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

Placebo Tests - Randomized Treatment Test

To further establish the robustness of our results, we perform a randomized treatment test [Bertrand et al., 2004]. For this test, we randomly reassign the restaurants to new treatment and control groups and estimate the regression coefficient. By repeating this estimation for 1,000 iterations, we obtain a distribution of resulting coefficients, as demonstrated in Figure 2.2. The figure shows that the distribution is centered around zero, indicating that if the treatment was randomly assigned, the resulting impact on log(number of reviews) and average star ratings of would not exist. To test this claim, we conduct a t-test to validate whether the mean of the distribution is statistically different than zero. We obtain p-values of 0.28 and 0.85 respectively, indicating that we fail to reject the hypothesis. Therefore, it is highly likely that the positive and significant coefficients for *ArtifactInfluence* we observe in our main results are valid.

Note that the coefficient value for the same specification we estimated in the main result is 0.057 and 0.273, as seen in Tables 2.6 and 2.10. Assuming that the coefficients (in Figure

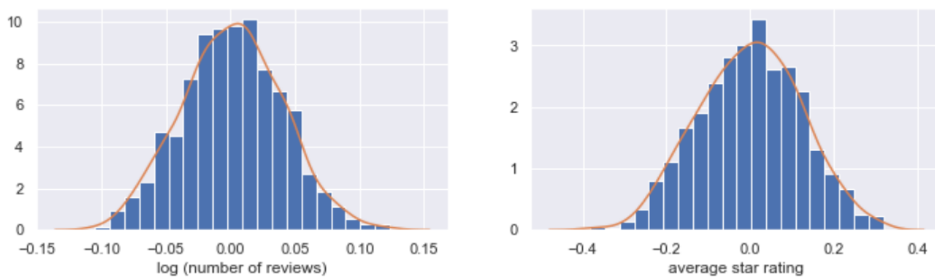


Figure 2.2.: Distribution of Coefficients for randomized treatment test

2.2) follow a Normal distribution, the associated probabilities for our DVs log(number of reviews) and Average of restaurant reviews are 0.069 and 0.012 respectively. This means that if the treatment was randomly assigned, the probability of our observed coefficients are 6.9% and 1.2%, providing further evidence for the significant result on consumer engagement and perception.

Placebo Tests on Pre-treatment Observations

Lastly, we conduct a placebo test to ensure that our results are indeed driven by the exogenous shock and not by any coincidence. If the main results are only driven by the release of Pokémon Go, no such effect should be observed in any pre-treatment periods. Therefore, we perform two falsification tests by altering the date of exogenous shock. For the first test, we introduce the 'fake' treatment by dividing the pre-treatment periods into two halves of 4 periods each. The estimates are reported in Table 2.25 under Placebo 1. We find no impact of *ArtifactInfluence* in this placebo specification. In addition, one may also argue that the results may be a function of an inherent unobserved seasonal trend prevalent in the treatment group. To rule out such possibilities, the second falsification test introduces the 'fake' treatment on the same day, but a year before the actual treatment (i.e., July 7, 2015). If, in fact, our results are seasonal, this placebo test should yield a positive significant coefficient for *ArtifactInfluence*. The results for this analysis are presented in Table 2.25 under Placebo 2. Here, we observe that the coefficient on *ArtifactInfluence* is statistically insignificant, suggesting that there is no evidence that our main result is driven by a seasonal trend.

Table 2.25.: The effect of an in-game artifact on nearby restaurants

	Placebo 1: Pre-treatment placebo		Placebo 2: Treatment set in 2015	
	log(num of reviews)	average star rating	log(num of reviews)	average star rating
ArtifactInfluence	0.001 (0.031)	0.097 (0.085)	-0.020 (0.019)	-0.088* (0.048)
Crime	-0.001 (0.003)	0.007 (0.009)	-0.001 (0.003)	-0.006 (0.007)
Weather	0.066** (0.027)	-0.023 (0.094)	-0.004 (0.019)	-0.020 (0.057)
Constant	-0.916 (0.567)	4.600** (1.931)	0.259 (0.410)	5.140*** (1.296)
Restaurants Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
R-squared	0.44	0.42	0.64	0.67
N	5232	2879	9776	5471

Note: Standard errors in parentheses are robust and clustered by restaurant.
* $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

2.7 Discussions and Conclusions

Pokémon Go, an augmented-reality-based mobility game, is wildly popular. This game has been significantly effective in shaping user behavior both positively and negatively. Recently, the game developer has partnered with major restaurant chains such as McDonald's in Japan and Starbucks in the United States to place the in-game virtual artifacts within the retail stores. In this paper, we study the economic implications of Pokémon Go on related businesses.

We collected a dataset on restaurant reviews and the geo-location of Pokémon Go artifacts (PokéStops and Gyms). Then, we use the propensity score matching and difference-in-differences regression analysis to empirically investigate how the presence of an in-game artifact affects restaurants located within its radius. We operationalize our research agenda by using restaurant reviews as a proxy to measure consumer economic behavior; the number of reviews to measure consumer engagement; and the average star ratings to measure consumer perception of the restaurants. We also examine how the characteristics of the restaurant, such as its affordability, popularity, and area crowdedness, moderate the effect that in-game artifacts have on the restaurants.

We find that restaurants located near an in-game artifact do indeed observe an increase in consumer engagement compared with restaurants that have no in-game artifacts nearby. In addition, restaurants located near an in-game artifact also experienced improved consumer perception after Pokémon Go was released. Meanwhile, the effect on consumer perception is not significantly different among diverse restaurants while the effect on consumer engagement varies. Specifically, less expensive and less popular restaurants appear to enjoy the benefit of in-game artifacts more, particularly in terms of increased consumer engagement. We also conduct several diagnostic tests to demonstrate that the effect we observe can be attributed to the introduction of Pokémon Go and that there is no fundamental change in terms of consumer behavior during the study period.

In terms of contribution, this research provides the first empirical evidence of the economic impact that Pokémon Go, or augmented-reality games in general, have on associated businesses. Unlike the past empirical studies that examine the economic implications of location-based applications, mobile games, and gamification practices, Pokémon Go combines several technologies like augmented-reality and location-based gaming that are usually distinctive, thus making it difficult for academic researchers and practitioners to extrapolate the potential outcomes from the findings of the previous related studies. In addition, our results yield significant managerial implications by highlighting the moderation role of business characteristics on the effect of Pokémon Go's in-game artifacts on nearby restaurants. Our findings emphasize the importance of customer conversion practices, since the increase in foot traffic does not guarantee an increase in the number of customers, especially for more expensive restaurants. In that regard, this study assists business managers in developing appropriate policies for governing any partnership between their businesses and Pokémon Go (or augmented-reality games in general) by providing empirical insights on the economic implications of such a partnership. These insights are crucial since Pokémon Go is now adding more businesses to their partnership agreement and is potentially looking to extend the agreement to local businesses. Also, such a partnership can be costly, and the impact on the firm's intrinsic value (e.g., consumer perception on the business) can affect business performance in the long run. Moreover, business managers can extrapolate our results to infer the impact that Pokémon Go may have on the revenue of their business since previous literature has established a strong connection between our dependent variables (i.e., total number of reviews and average star ratings) with business performance [e.g., Chevalier and Mayzlin, 2006, Luca, 2016].

Our research is not, however, without limitations. This work analyzes the data from the city of Houston, Texas, a major city in North America. There could be some cultural differences in terms of how consumers react to the presence of Pokémon Go's in-game artifacts, which is a potential avenue for future research. Also, we only analyze the data up to four months after the release date of Pokémon Go. Another interesting research avenue would be to investigate the longer-term effects of Pokémon Go. However, it is important to note that Pokémon Go introduced multiple changes to the game after December 2016 (e.g., many in-game artifacts were added and removed dynamically, the introduction of the sponsored partnership program, the change in the Gym system). Therefore, a research methodology must be carefully chosen to control the effect of these policy changes. Lastly, another future research avenue would be to study directly the impact of Pokémon Go on business revenue.

3. USING MACHINE LEARNING FOR MODELING HUMAN BEHAVIOR AND ANALYZING FRICTION IN GENERALIZED SECOND PRICE AUCTIONS

3.1 Introduction

The online ad market has seen spectacular growth in recent years. For example, the revenue generated by platforms such as Google, Bing, and Yahoo exceeded \$92 billion in 2017 [Statista, 2017]. Generally, these platforms are believed to have reduced the cost of participation and allow more advertisers to enter these markets. Furthermore, advances in automation and artificial-intelligence tools (e.g., auto bidders) have contributed to a substantial reduction in the cost of bid adjustments – i.e., friction – once the advertiser has entered the market. Even then, prior literature has not studied the role that such friction costs have on the sponsored-search-auction outcomes.

In this paper, we study the role of frictions in the outcome of the generalized second price auction (henceforth GSP). Seminal theoretical works such as Edelman, Ostrovsky, Schwarz (2007) [Edelman et al., 2007] and Varian (2007) [Varian, 2007] have provided a structured approach of analyzing this context. A few papers have focused on deviations from the basic theoretical model [e.g., Jerath et al., 2011, Simonov et al., 2018]. Yet, none have analyzed the role of frictions in explaining commonly observed deviations such as overbidding [e.g., Cooper and Fang, 2008, Kamijo, 2013, McLaughlin and Friedman, 2016, Noti et al., 2014, Sheremeta, 2010]. In particular, our focus is on the friction associated with the bidding process, which has been decreasing with availability of advanced tools like auto-bidders, etc. Specifically, we study the following research questions: Do frictions lead to an increase or decrease in overbidding? What are the consequences for the auctioneer, for the advertiser, and for the allocative efficiency of the GSP?

These questions cannot be studied empirically. The secondary data do not have the advertisers' private valuations, so the identification can become a problem. Therefore, we study the above questions through a combination of computational and experimental approaches. Specifically, we first investigate bidding behaviors and allocative efficiency using a computational model involving reinforcement-learning agents. The computational model provides several testable predictions about the effect of friction costs. We subsequently validate these hypotheses using a human-subject experiment in a controlled laboratory setting. Finally, after establishing the validity of our computational model, we use simulations to provide additional insights into the role that frictions play in the markets that we cannot feasibly (or practically) investigate with human-subject experiments.

For our computational approach, we use a well-established model from the machine-learning literature that dates back to the 1980s. In particular, our computational agents implement a version of Q-learning [Sutton and Barto, 1998] in an environment akin to Edelman, Ostrovsky, Schwarz (2007) [Edelman et al., 2007].[1] The market frictions are modeled as additional costs that the participants incur during their bid-adjustment process. We find the following key results through the machine-learning model: (a) Contrary to the theoretical models, the lowest-valued advertisers submit bids higher than their private valuation; (b) this overbidding phenomenon leads to allocative inefficiencies in the market; and (c) the allocative efficiency may increase as the frictions increase. We confirm these results experimentally. Thus, in some regards, our computational model may be perceived as a digital twin representation of advertisers in GSP.

The rest of the paper is organized as follows: In Section 3.2, we outline the previous literature that relates to our paper. In Section 3.3, we present details of the auction environment and develop the hypotheses using the agent-based model. In Section 3.4, we present

[1] Q-learning is extensively used in machine-learning and deep-learning applications, including Google's Deepmind solving AlphaGo.

the experimental design. In Section 3.5, we present the data and main results of the human-subject experiment. Finally, in Section 3.6, we summarize our research findings and discuss future research directions.

3.2 Literature

Our study contributes to three streams of literature. First, we contribute to the literature on sponsored search advertisement and auction mechanisms. Second, we contribute to a growing body of literature in Information Systems that uses economic experiments. And third, we contribute to the emerging literature that uses machine-learning models to study market outcomes. Next, we provide a brief review for each of the three streams of literature.

3.2.1 Sponsored Search Keyword Auctions

The sponsored search auctions have attracted tremendous interest in the IS literature. Several empirical studies have focused on the evolution of bidding strategies and the resulting impact on sponsored search metrics [e.g., Animesh et al., 2010, 2011, Ghose and Yang, 2009]. The bidding strategies have also been the focus of Zhange et al (2011) [Zhang and Feng, 2011], who introduce a dynamic model to study the cyclic bidding by the advertisers. A number of theoretical papers have expanded on the works of Edelman et al (2007) [Edelman et al., 2007] and Varian (2007) [Varian, 2007] in order to improve the auction outcomes [e.g., Amaldoss et al., 2015, Chen et al., 2010, Edelman and Schwarz, 2010, Varian, 2009] or evaluate alternative mechanisms [e.g., Feng et al., 2007]. Though most of the works consider the auction for an individual keyword, some studies explore the bidding process for multiple keywords [e.g., Du et al., 2017] and the interaction between organic results and the sponsored search results as competing information sources [e.g., Agarwal et al., 2015, Xu et al., 2012]. Furthermore, recent works have investigated more advanced variations of the auction environment including auctions with unknown click-through rates [Devanur and

Kakade, 2009, Gatti et al., 2012], auctions with dependent click-through rates [Deng and Yu, 2009, Kempe and Mahdian, 2008, Simonov et al., 2018] and auctions with budget constraints [Arnon and Mansour, 2011, Zhou et al., 2008], etc. Qin et al (2015) [Qin et al., 2015] provide a comprehensive review of the sponsored search auction literature.

Our paper contributes to this vast literature by studying the GSP auction outcomes and bidding behavior in the presence of market frictions. In particular, the recent advances in communication technology have resulted in significantly reduced informational frictions in the sponsored search auctions. Further, the proliferation of AI tools (e.g., auto-bidders) have further contributed to reduction of frictions. Although frictions have been studied in different contexts including trade [Allen, 2014, Hou and Moskowitz, 2005], stock markets [Capasso, 2008], housing markets [Anenberg, 2016], and labor markets [Bassi and Nansamba, 2017], we aim to study the role of frictions in the context of sponsored search auctions. In particular, we incorporate these frictions into the model presented in Edelman, Ostrovsky, Schwarz (2007) [Edelman et al., 2007]. We then employ a twofold strategy of investigating the auction outcomes using machine-learning computational agents in combination with human-subject experiments. A brief review of literature on economic experiments and computational methods is next.

3.2.2 Economic Experiments in IS

The use of laboratory experiments to test theoretical insights and guide the design of systems has gained substantial traction in the IS field. Following the early work, which includes the development of the technology-acceptance model by Bagozzi (1992) [Bagozzi et al., 1992] and the evaluation of the task-technology fit model by Goodhue et al (1995) [Goodhue and Thompson, 1995], recent literature has expanded the use of experiments to a variety of IS applications, including privacy [e.g., Brandimarte et al., 2013, Tsai et al., 2011], bundle pricing [e.g., Goh and Bockstedt, 2013], and recommender systems [e.g., Adomavicius et al., 2013a, 2014]. In a recent review of the experimental literature in IS, Gupta et al (2018)

[Gupta et al., 2018] argue that experiments can yield meaningful results that overcome the limitations faced by empirical and theoretical studies. In the context of our study, to make any conclusions about allocative efficiency or bidding behavior, we must observe the private valuations of the auction advertisers, which is not possible using real-world data.

The experimental approach has been particularly fruitful in studying auctions [e.g., Adomavicius et al., 2006, 2012, 2013b, Bapna et al., 2010, Cason et al., 2011, Sanyal, 2016]. Several early experiments on behavior in auctions report that subjects rarely choose the dominant strategy [Kagel and Levin, 2001, Kagel et al., 1987, 1995]. In particular, the robust finding in this literature is that human subjects regularly bid higher than their value. Closest to our paper are four recent studies that investigate GSP auctions experimentally: Fukunda et al (2013), Noti et al (2013), McLaughlin et al (2013), Che et al (2017) [Che et al., 2017, Fukuda et al., 2013, McLaughlin and Friedman, 2016, Noti et al., 2014]. With the exception of Mclaughlin et al (2013) [McLaughlin and Friedman, 2016], these studies find significant overbidding behavior by the participants. The primary question in all of these studies, however, is different from ours. Whereas prior studies have focused on the comparison of GSP to VCG mechanisms, we investigate the role of frictions in improving outcomes of the GSP auction. In particular, we focus on how the presence of market frictions may mitigate overbidding behavior and lead to higher allocative efficiency. In addition, the use of machine-learning agents in combination with human-subject experiments is a distinctive feature of this paper.

3.2.3 Agent-based Computational Models

In addition to theoretical, empirical, and experimental approaches, agent-based simulations have been successfully used to provide insights in the context of allocation problems. For example, Guo et al (2012) [Guo et al., 2012] analyze bundle trading markets for distributed resource allocations. Ketter et al (2012) [Ketter et al., 2012] study trading agent competition in a supply-chain context, in which a need exists to make product-pricing and inventory-resource-allocation decisions in real time. In the context of auctions, Bichler et al [Bichler et al., 2013] study the efficiency of combinatorial clock auctions, Kiose et al (2015) [Kiose and Voudouris, 2015] study power auctions, and Guerci et al (2014) [Guerci et al., 2014] investigate sequential Dutch auctions.

To be able to replicate (imitate) human behavior using computer agents, the agents need to adopt a learning process. For our study, we employ Q-learning [Watkins and Dayan, 1992] to model the behavior of advertisers in the GSP environment. We chose this approach for several reasons. First, Q-learning has been used to investigate learning in multiple-agent environments [e.g., Bowling and Veloso, 2001, Greenwald et al., 2003, Littman, 1994, Sandholm and Crites, 1996]. Second, Q-learning has been used to match behavioral regularities observed in human subject experiments [e.g., Rosokha and Younge, forthcoming]. Third, Q-learning algorithms have been successfully applied to investigate the efficacy of information revelation and structural properties in a variety of auctions [Greenwald et al., 2010]. Finally, the reinforcement-learning approach is not new to the GSP. Chen (2016) [Chen et al., 2016], establish a connection between machine-learned models and the game-theoretic properties of a system using real data from a sponsored-search-advertising platform.

3.3 Computational Analysis and Hypotheses Development

In this section, we first present the environment (Section 3.3.1); second, we present details of our implementation of the agent-based model (Section 3.3.2); and finally, we provide the results of our simulations and state the main hypotheses (Section 3.3.3).

3.3.1 Core GSP Model

To study the problem in a structured manner, it makes sense to build from a theoretical model. However, we are not aware of any universally accepted theoretical model in GSP as certain assumptions have been shown to be violated. Therefore, we consider a specialization of, arguably, the most well-known paper — Edelman et al. [2007] — and incorporate elements related to frictions. In particular, the GSP environment contains $J = 3$ advertisers, each with a unit demand, participating in an auction for $K = 2$ ad slots. Each advertiser submits only one bid. The advertisers may be placed in either of the slots (note that one advertiser will fail to appear in any of the slots). Let α_k represent the click-through rate for the k-th ad slot. Without the loss of generality, we assume $\alpha_1 = 1 > \alpha_2 = \alpha > \alpha_3 = 0$. The first slot is more desired and has a higher click-through rate than the second slot.[2] The third slot, which does not exist, is assumed to have a zero click-through rate for ease of representation. Thus, a higher value of α means that the two ad slots are more similar.

Conditional on the click-through, advertiser j realizes a value v^j and, without loss of generality, we assume $v^1 > v^2 > v^3$. In our implementation, we assume that the valuations are private information and drawn from a uniform distribution. We define a rank function $j \to (k)$ that maps an advertiser j to an ad-slot k, based on the descending order of bids.[3] Therefore, we represent the valuation realized by the k-th highest advertiser as $v^{(k)}$ and her corresponding bid as $b^{(k)}$. The key element of the GSP is that each winning advertiser pays an amount equal to the next highest bid. Therefore, the payoff for the k-th highest-bidding advertiser (allotted to the k-th slot) is given by $\alpha_k(v^{(k)} - b^{(k+1)})$.[4]

In this paper, we focus on two metrics of interest. The first metric of interest is the *allocative efficiency* of the auction. This metric captures the amount of realized social welfare relative to the maximum possible value. In particular, given the setup above, we define the allocative efficiency as:

$$\Psi = \frac{v^{(1)} + \alpha v^{(2)}}{v^1 + \alpha v^2}. \tag{3.1}$$

[2]Anecdotally, ads in the higher slots tend to receive more clicks, making them more attractive to the advertisers.

[3]Note that search engines have evolved to calculate a quality score based on the previous performance of the ads and the bid amount placed by the advertiser. These quality scores are being used to determine the slot to be assigned to the advertiser. For our work, we consider a simplified case in which the slot allocation is based only on bids.

[4]For ease of notation, we assume that $b^{(4)} = 0$.

The second metric of interest is the *bid-to-value ratio* for each of the advertisers. This metric captures behavior at the individual level. Specifically, we define the bid-to-value ratio for rank k as:

$$\Omega^{(k)} = \frac{b^{(k)}}{v^{(k)}}. \tag{3.2}$$

Note that whereas Ω^j is calculated at the individual level, Ψ is calculated at the market level.

We model *frictions* as an additional cost C^j incurred by advertiser j from revising their bids. That is, the payoff for advertiser j is

$$\pi^{(k)} = \alpha_k(v^{(k)} - b^{(k+1)}) - C^{(k)},$$

where C^j could, for example, correspond to implicit costs, such as the efforts taken by the advertisers to repeatedly change their bids, or explicit costs, such as fees charged by the platforms. Notice that in the latter case, the allocative efficiency is equivalent to the overall efficiency of the market.

The equilibrium analysis from Edelman, Ostrovsky, Schwarz (2007) [Edelman et al., 2007] provides several theoretical predictions for the case in which $C^j = 0$. In particular, regarding the allocative efficiency, the theory predicts that the outcome of the auction will be fully efficient (i.e., $\Psi = 1$). Regarding the bid-to-value ratio, the theory does not make a precise prediction, because infinitely many equilibria are possible. Nevertheless, the assumption that the lowest-valued advertisers will bid their true value (i.e., $\Omega^{(3)} = 1$), which is a weakly dominant strategy for those players, is common. This assumption in turn leads to a prediction regarding the bid-to-value ratio and the slot-similarity parameter for the medium-valued advertisers (i.e., $j = 2$). Specifically, it is straightforward to derive that $\Omega^{(2)}$ is decreasing in α.[5] Crucially, theory makes no predictions regarding the behavior of the highest-valued

[5]In the constructed equilibrium, the second advertiser submits a bid satisfying the following condition: $\alpha(v^2 - b^3) = v^2 - b^2$. By assuming $b^3 = v^3$ (as is done for their equilibrium derivation), we obtain: $\frac{b^2}{v^2} = 1 + \alpha(\frac{v^3}{v^2} - 1)$, where $\frac{v^3}{v^2} < 1$ by construction.

advertisers (i.e., $j = 1$), and is at odds with experimental evidence on overbidding mentioned above. Furthermore, the existing theory does not incorporate friction costs for the case of $C^j > 0$. Therefore, we turn to a computational model to develop hypotheses for the outcomes of the GSP auction.

3.3.2 Agent-based Implementation of the GSP Environment

Consistent with the theoretical underpinning, we allow a group of $J = 3$ agents to compete for $K = 2$ ad-slots. The agents learn how to bid using the Q-learning model, described next.

Q-Learning Model Details

The objective of a Q-learning agent is to learn an optimal policy that maximizes the expected reward. Fundamental to the algorithm are the Q-values, denoted as $Q(s, a)$, which represent the value of taking an action a in state s. The Q-values are learned over time using a reinforcement-learning process. Specifically, suppose at time t, the agent selects an action a_t, observes a reward π_t, and enters a state s_{t+1}. Then, the Q-value is updated as follows:

$$Q^{new}(s_t, a_t) \leftarrow (1 - \delta)\, Q(s_t, a_t) + \delta\, (\pi_t + \gamma\, max_a\, Q(s_{t+1}, a)), \tag{3.3}$$

where $0 \leq \delta \leq 1$ is the learning rate and $0 \leq \gamma \leq 1$ is the discount factor.

Given Q-values, the agent chooses an action (i.e., bid) using a policy function. We use the *softmax* policy function, which is common in the literature. Specifically, the action is determined using the Boltzmann probability distribution: $\frac{e^{\lambda Q(s,a)}}{\sum_{a_i} e^{\lambda Q(s,a_i)}}\ \forall a_i \in A(s)$, where $A(s)$ is the set of actions available in state s, and λ captures the amount of exploration. In this way, Q-learning is a type of stochastic learning model that selects more profitable actions more often.

We implement the Q-learning algorithm in our GSP context as follows. A group of $J = 3$ agents compete for $K = 2$ ad-slots over $M = 2,000$ matches. Each match lasts $T = 100$ time periods, indexed by t. At the beginning of each match ($t = 0$), private values v^j are randomly drawn from $\mathcal{U}\{1, 10\}$. The values are retained for the duration of the match. For every t, the agent chooses to place a bid b_t^j from $\mathcal{U}\{0, 10\}$. As mentioned earlier, the chosen bid depends on the state s that the agent is in. In our implementation of the GSP environment, the state s_t is a tuple of the agent's private valuation and the current bid: (v^j, b_{t-1}^j). That is, the agent j decides on a bid b_t based on the private value, v^j, and own previous bid, b_{t-1}^j. Importantly, we assume that the friction cost of C is incurred every time the agent changes the bid from period $t-1$ to t (i.e, if $b_t \neq b_{t-1}$), and that this cost is a constant and the same across all agents.

Table 3.1.: Summary of Q-learning variables and parameters for GSP

States and actions	
State: $s_t^j \rightarrow$	(v^j, b_{t-1}^j)
Action: $a_t^j \rightarrow$	b_t^j
Reward: $\pi_t^j \rightarrow$	$\pi_t^{(k)} = \alpha_k(v^{(k)} - b_t^{(k+1)}) - C^{(k)}$
Environment parameters	
$\delta \rightarrow$	0.1
$\gamma \rightarrow$	0.99
$\lambda \rightarrow$	1
Treatment variables	
$C \rightarrow$	$\{0.0, 0.5, 1.0\}$
$\alpha \rightarrow$	$\{0.2, 0.5, 0.8\}$

Notes: Recall that a rank function maps agent $j \rightarrow$ slot (k).

At any given t, after all bids are submitted, the slots are allocated in the order of the bids (with ties broken randomly). Each agent is assumed to gain $\alpha_k v^{(k)}$ but incurs $\alpha_k b^k$ as payment to the intermediary and $C^{(k)}$ as the bid-adjustment cost. At the end of the match ($t = 100$), the bids and the outcomes (bid-to-value ratio and the allocative efficiency) are recorded. To derive comparative static predictions, we execute all these steps for various combinations of C and α, specifically, $C \in \{0.0, 0.5, 1.0\}$ and $\alpha \in \{0.2, 0.5, 0.8\}$. Further details on our implementation of the Q-learning model as well as robustness checks for different parameter values are presented in Appendix A.1.

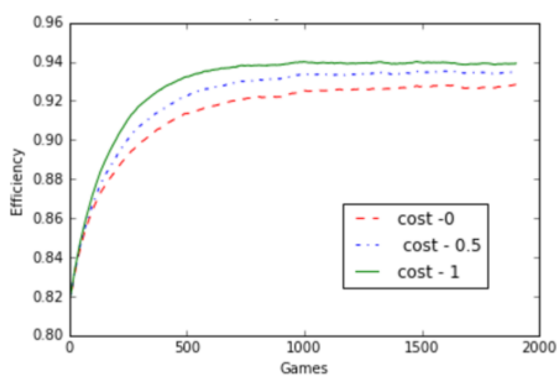
3.3.3 Computational Predictions

In this section, we present results of our learning-model simulations. In particular, in Section 3.3.3, we present the market-level outcomes, whereas in Sections 3.3.3 and 3.3.3, we consider individual-level outcomes.

Allocative Efficiency

Panel (a) of Figure 3.1 presents the evolution of the allocative efficiency, Ω, over the learning horizon, whereas panel (b) of the figure presents a more detailed breakdown of the converged outcomes.

(a)



(b)

	$C = 0.0$	$C = 0.5$	$C = 1.0$
$\alpha = 0.2$	0.944	0.952	0.960
$\alpha = 0.5$	0.95	0.956	0.960
$\alpha = 0.8$	0.951	0.957	0.961
Average	0.948	0.955	0.960

Notes: (a) Evolution of allocative efficiency throughout the learning horizon (for $\alpha = 0.5$). (b) Allocative efficiency in converged markets (matches 1,800-2,000).

Figure 3.1.: Allocative Efficiency

Figure 3.1a shows that, initially, allocative efficiency is the same across the three cost treatments (around 0.85). However, as agents learn, the efficiency increases and the differences among the three cost scenarios appear. In particular, the main observation from the figure is that allocative efficiency is higher with higher costs. Figure 3.1b shows that this finding is true regardless of α, although when alpha is low, the increase is higher. We summarize these observations with Hypothesis 1.

Hypothesis 1: *Allocative efficiency of the market increases as friction costs increase.*

Exploratory Behavior

Table 3.2 presents the number of bid adjustments that agents make, on average, across $N = 10,000$ simulations. The three panels of Table 3.2 present the number of bid adjustments for each of the three agents, $j \in \{1, 2, 3\}$, sorted based on their private values and labeled as highest-valued, medium-valued, and lowest-valued agents, respectively.[6] The rows correspond to different values of α, whereas the columns within each panel correspond to different values of C.

[6] For example, if the three participants were assigned private values of 7,4,2, then the participant with the private value of 7 would be considered highest-valued, the participant with the private value of 4 would be considered medium-valued, and the participant with the private value of 2 would be considered lowest-valued.

Table 3.2.: Number of Bid Adjustments

	(a) Highest-valued agent			(b) Medium-valued agent			(c) Lowest-valued agent		
	$C = 0.0$	$C = 0.5$	$C = 1.0$	$C = 0.0$	$C = 0.5$	$C = 1.0$	$C = 0.0$	$C = 0.5$	$C = 1.0$
$\alpha = 0.2$	48	19	7	49	18	8	67	45	29
$\alpha = 0.5$	51	25	11	45	15	6	57	32	20
$\alpha = 0.8$	53	32	18	45	18	8	52	26	15
Average	51	25	12	46	17	7	59	34	21

Notes: Results are rounded to nearest integer. The maximum number of adjustments can be 100.

Notice that the number of bid adjustments is a simple measure of exploratory behavior by the agents. Thus, the key takeaway from Table 3.2 is that the number of bid adjustments decreases as the friction costs increase. This finding is intuitive – when the exploration becomes costlier, the agents explore less. We expect to observe a similar result with our human subjects and summarize this prediction with Hypothesis 2.

Hypothesis 2: *Lower costs lead to more exploration.*

Bidding Behavior

Table 3.3 presents outcomes in terms of the bid-to-value ratios. Similarly to Table 3.2, the three panels of Table 3.3 present the average bid-to-value ratios for each of the three agents, $j \in \{1, 2, 3\}$, sorted based on their private values. Again, the rows corresponds to different values of α, whereas the columns within each panel correspond to different values of C.

Table 3.3.: Bid-to-Value Ratios

	(a) Highest-valued agent			(b) Medium-valued agent			(c) Lowest-valued agent		
	$C = 0.0$	$C = 0.5$	$C = 1.0$	$C = 0.0$	$C = 0.5$	$C = 1.0$	$C = 0.0$	$C = 0.5$	$C = 1.0$
$\alpha = 0.2$	0.842	0.852	0.852	0.913	0.918	0.901	1.269	1.232	1.11
$\alpha = 0.5$	0.753	0.756	0.759	0.826	0.829	0.826	1.083	1.056	0.996
$\alpha = 0.8$	0.686	0.688	0.688	0.774	0.777	0.771	0.982	0.969	0.910
Average	0.760	0.765	0.766	0.838	0.842	0.833	1.111	1.086	1.005

Notes: $\Omega^j > 1$ would mean that agent j is overbidding.

There are three takeaways from Table 3.3. The first takeaway is that the bid-to-value ratios are highest for the lowest-valued agents. Furthermore, for the lowest-valued agents, the bid-to-value ratios are greater than 1.0, on average (i.e., the agents submit bids more than their valuation). The intuition for this result from our computational model is that the lowest-valued agents are *not* likely to win the auction even if they bid slightly more than their true value, and hence earn zero. Recall that, given that the agents implement the softmax action-selection policy, actions with similar payoffs are equally likely. Thus, bids above the true value would yield an expected payoff that is comparable to bidding the true value. We summarize this prediction with Hypothesis 3.

Hypothesis 3: *Bid-to-value ratio is higher for lower-valued agents.*

The second takeaway from Table 3.3 is that costs play a role in the bid-to-value ratios *only* for lowest-valued agents. Specifically, the bid-to-value ratios of the highest-valued and medium-valued agents stay remarkably consistent independent of the costs, whereas the bid-to-value ratios for the lowest-valued agents drop by approximately 10% for each of the three values of α. These results suggest that friction moderates the overbidding, particularly for the lowest-valued advertisers. We summarize this prediction with Hypothesis 4.

Hypothesis 4: *For the lowest-valued agents, the bid-to-value ratio increases as friction costs decrease.*

The last takeaway from Table 3.3 is regarding the the role of α. In particular, the table shows that as α increases, the bid-to-value ratio decreases for all agents, regardless on their respective private value ranks. We summarize this prediction with Hypothesis 5.

Hypothesis 5: *The bid-to-value ratio decreases as α increases.*

Several points are important to reiterate. First, with the exception of Hypothesis 4, the theory of Edelman, Ostrovsky, Schwarz (2007) [Edelman et al., 2007] does not provide predictions that correspond to those obtained with our agent-based model. Second, the predictions obtained in this section are not intended as point predictions; instead, the takeaways from the tables should be qualitative in nature. Finally, the predictions are based on a relatively simple learning framework that is independent of the other behavioral factors that may also play a role when humans participate in the auction. Thus, although we expect the general trends observed in the computational model to hold in a human-subject experiment, psychological factors such as auction fever [Adam et al., 2011], spite [Cooper and Fang, 2008], and joy-of-winning [Kamijo, 2013] among non-winners also can further strengthen or weaken these results.

3.4 Experimental Design and Administration

This section describes the experimental design of the auction described in Section 3.3.2. The nomenclature used below is consistent with our usage when conducting the experiments and is somewhat different from the description above. We have used different nomenclature in the experiment so that it is intuitive for the subjects. In particular, we refer to the advertisers as *participants* in the experiment, the ad slots as *goods* that the participants bid for, and the auction itself as a *match* that participants bid in. As is the norm with economic experiments, the amount of money that participants make at the end of the experiment depends on their performance in the experiment.

3.4.1 Treatments

Our primary objective is to investigate the role of friction cost on the outcomes of the GSP. Therefore, the two main treatments of the experiment are with respect to the costs of the bid adjustments imposed on the participants. Specifically, the experiment consisted of two *between-subject* treatments with respect to the cost of adjustment, C. We also set out to vary α – the correlation between the value of the top two slots. However, we varied α within treatment. That is, during the experiment, each participant was likely to experience multiple α's, but the same C. Table 3.4 presents a summary of the two treatment dimensions.

Table 3.4.: Treatments Summary

Treatments	Parameter Varied	Description
$Between - Subjects$	$C \in \{0.0, 0.1\}$	*Costless* or *Costly* bid adjustment within matches
$Within - Subjects$	$\alpha \in \{0.2, 0.5, 0.8\}$	*Value of the second good* as a fraction of the first good

The between-subject treatments were: *costless* bid adjustment ($C = 0$) and *costly* bid adjustment ($C = 0.1$). In the costless treatment, subjects incurred a cost of $C = 0.0$ for changing their bid during the match. In the costly treatment, subjects incurred a cost of $C = 0.1$ for changing their bid during the auction. In both cases, however, subjects could place the initial bid at no cost. Because subjects incurred the cost every time they changed their bid, they could incur multiple costs in the same match. In particular, a subject could make as many adjustments as she wanted until the time for the match expired. The within-subject treatments were *low* correlation ($\alpha = 0.2$), *medium* correlation ($\alpha = 0.5$), and *high* correlation ($\alpha = 0.8$). All participants in a group had the same $\alpha \in \{0.2, 0.5, 0.8\}$ for the duration of each.

3.4.2 Matches

Each session consisted of $M = 10$ matches. At the beginning of each match, participants were randomly split into groups of three ($J = 3$) and remained so until the end of the match. The regrouping for the next match was random to avoid any systematic learning about participant behaviors. Earnings for the experiment were the sum of payoffs across all 10 matches.

To avoid the end-of-match effects associated with the fixed duration of a match, we opted for random termination. Specifically, each match lasted at least 20 seconds, after which, there was a 1% chance that the match would terminate each second. Thus, the expected duration of each match was two minutes. To ensure a valid comparison across sessions, the same sequence of seconds across matches was used in every session.[7] We summarize this design choice with Design Remark 1.

Design Remark 1: *Random termination protocol.*

For each match, the participants were provided with randomly drawn private values for good 1. We then obtained the value of good 2 by multiplying the value of good 1 and α. Parameters for the initial four matches were drawn at random *without any restriction.* However, in matches 5 through 10, we aimed to provide a clean comparison among the treatments. Therefore, we used common seeds to generate the same random values across the two treatment dimensions. This approach ensured that any learning that took place in the early matches was not systematically biased and allowed us to compare across different

[7]Table A.5 in the Appendix presents the match duration for each of the ten matches.

values of α using the later matches. We summarize this design choice with Design Remark 2.

Design Remark 2: *We used common random numbers in matches 5 through 10 such that for*

- *Each match, $m \in \{5, ..., 10\}$, all groups had the same three valuations $\{v_m^1, v_m^2, v_m^3\}$.*

- *Each match, $m \in \{5, ..., 10\}$, there was at least one group for each value of α.*

3.4.3 Auction Details

At the beginning of a match, each participant j submits a bid b^j at no cost. Participants can then revise their bids in continuous time during the match. Participants can lock the bids to see the associated outcome and payoff with the current combination of bids. Specifically, if her b^j bid is the highest, then she would get the first good and pay the amount equal to the second-highest bid (Recall $\alpha_1 = 1$) minus the friction costs incurred during the match $(b^{(2)} - C^{(1)})$. If her bid is the second highest, then she would get the second good and pay the amount equal to the third-highest bid minus friction costs incurred times α, that is, $\alpha(b^{(3)} - C^{(2)})$. If her bid is the lowest, she wouldn't receive any good and would pay nothing. We announced that the α would be the same for all participants in the group during the instructions to ensure common knowledge of this fact.

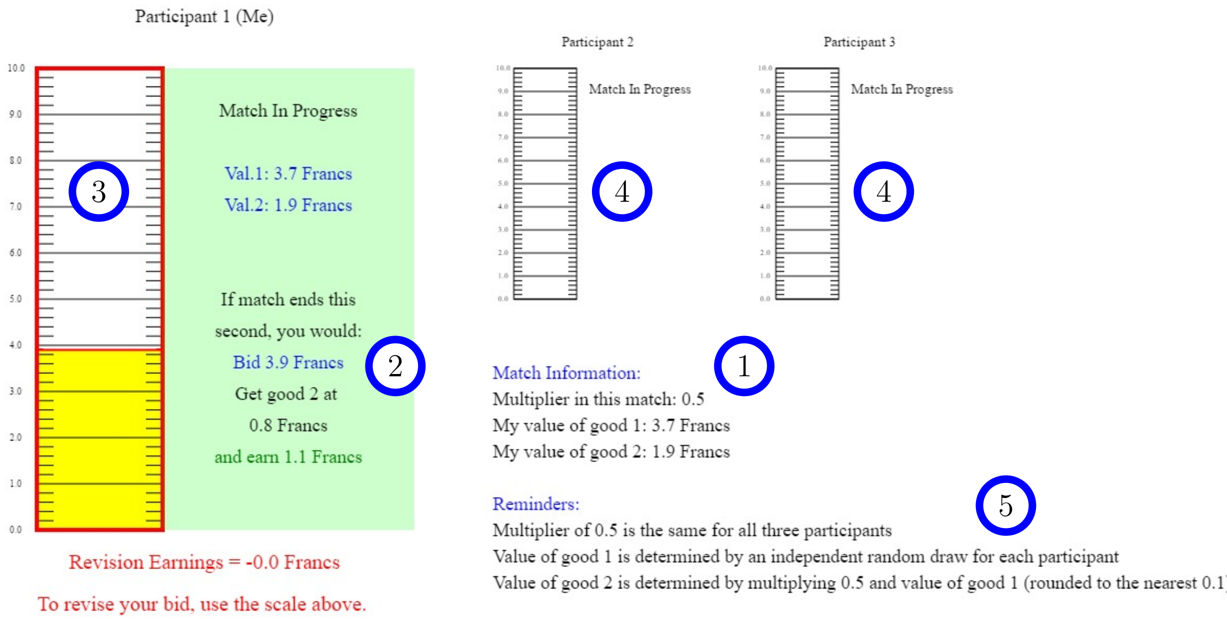
3.4.4 Experimental Interface

The experiment was conducted using an interface that was programmed by the authors. The interface implements the continuous-time feature of the auction with participants being able to make bid adjustments in real time. Figure 3.2 presents the screenshot of the interface. The participant's screen summarized information provided for that match (#1 in Figure 3.2), as well as current action and the outcome associated with this action (#2 in Figure 3.2).

To place or revise the bid, participants had to use the scale displayed on the left side of the screen (#3 in Figure 3.2).

We anticipated a potential problem involving mouse clicks. Specifically, mouse clicks could be used as a source of additional information about the behavior of other participants in this experiment. For example, a bid adjustment by subject i, if heard by subject j, could lead to subject j trying to check whether new profitable adjustments were available, by making one or more adjustments herself, which, in turn, could lead to many more clicks. This issue is particularly relevant because we ran multiple groups per session. Furthermore, as described earlier, the number of adjustments was one of the key differences between the treatments that we were looking for; therefore, comparing sessions that contained a large number of clicks (which could be clearly heard in the room) with sessions that didn't could be problematic. To resolve this issue, we implemented a *silent protocol*. Specifically, instead of clicking to select a new bid, subjects placed and adjusted their bid by moving the mouse back and forth across the scale border. This approach resulted in a quiet room throughout the experiment. Thus, subjects could not detect bid changes other than through the information provided on the screen. We summarize this design choice with Design Remark 3:

Design Remark 3: *Silent protocol.*



Notes: The screenshot shows: **(1)** Match information. This information is provided prior to the beginning of the match. **(2)** Action and the outcome associated with this action. The outcomes is updated live and depends on the actions of all three participants in the group. **(3)** Scale that is used to place and revise bids. **(4)** Scales for the other two participants. These scales remain blank until the match is over, at which point the actions of the other participants are revealed. **(5)** Reminders about the rules of the experiment.

Figure 3.2.: Experimental Interface

3.4.5 Experiment Administration

For the experiment, we recruited 138 participants using ORSEE software [Greiner, 2015] on the campus of Purdue University. We administered eight sessions of the experiment, with the number of participants in each session varying between 15 and 18.[8] Upon entering the

[8]After running the first four sessions (two for $C = 0.0$ and two for $C = 1.0$), we discovered an error in the way random seeds were generated by the software (recall that the seeds were used in the generation of common values across the groups in matches 5-10). The error was that for matches 5-10, the seed was incremented by 1 rather than 3. So for each group in period $t+1$, there were two values that were the same as in period t, and one new value (instead of three new values). The values were then randomly reassigned within the group. This means that there was an approximately 20% chance for a given subject to have the same value in two consecutive matches and an approximately 10% chance for a subject to have the same value in matches t and $t+2$. The bug was the same across the treatments, so in terms of comparison $C = 0.0$ versus $C = 1.0$ or in terms of comparison across α's, there should be no systematic effect between treatments. In terms of implications for the results, however, this means that subjects had more learning opportunities about the same values, which makes our findings about excessive experimentation and over-bidding conservative. We present the data broken down by the first four and last four sessions in Online Appendix A.4. As expected,

laboratory, participants were assigned to a computer terminal. All terminals were separated by physical barriers such that participants could not see choices made by other participants in the room. Participants remained anonymous throughout the experiment.

To ensure that subjects understood the interface and the bid-adjustment process, we took several steps. First, subjects were given a handout containing the instructions. An experimenter read them out loud to ensure common knowledge of the environment. Second, subjects had to complete six practice tasks that dealt with placing and modifying the bid. Subjects could proceed to the next task only after correctly completing the previous task. Third, the subjects had to go through five examples, which, to eliminate any bias, were generated at random. In the examples, subjects could practice placing and revising their bids for hypothetical actions by the opponents. Finally, subjects were provided with a calculator, pen, and paper for the duration of the instructions and the experiment. Thus, they were able to verify calculations in the instructions and practices tasks. Furthermore, subjects could make any necessary calculations during the experiment.

The above steps took approximately 20 minutes. Then, prior to each match, subjects were given time to review information for that match. Only after they were ready, did they placed their initial bid. Once everyone had placed the initial bid, the match began. The 10 matches took approximately 30 minutes to complete. After the 10 matches, subjects were paid in cash.

3.5 Results

The results section is organized as follows: First, in Sections 3.5.1-3.5.1, we test the hypotheses developed using the computational model. Second, having validated the computational model, we conduct several exercises to provide additional insights into the role that frictions play in the outcome of the GSP auction.

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we find the results obtained using data from sessions 1-4 to be consistent with results obtained using data from sessions 5-8.

3.5.1 Allocative Efficiency

Table 3.5 presents the allocative efficiency in our experiment. Recall that we focus on the outcomes in matches 5-10 to eliminate concerns about initial learning about the environment by the human subjects. In addition, for each match $m \in \{5, ..., 10\}$, private values across groups in session 1-4 and session 5-8 were the same, providing for a clean comparison across treatments.

Table 3.5.: GSP Efficiency

	$C = 0.0$		$C = 0.1$
$\alpha = 0.2$	0.926 (0.021)	$\overset{0.113}{\sim}$	0.967 (0.014)
	$\wr^{0.894}$		$\wr^{0.196}$
$\alpha = 0.5$	0.93 (0.023)	$\overset{0.016}{\ll}$	0.987 (0.005)
	$\wr^{0.204}$		$\wr^{0.912}$
$\alpha = 0.8$	0.967 (0.014)	$\overset{0.184}{\sim}$	0.988 (0.007)
	$\wr^{0.132}$		$\wr^{0.259}$
$\alpha = 0.2$	0.926 (0.021)		0.967 (0.015)
Average:	0.94 (0.012)	$\overset{0.001}{\lll}$	0.98 (0.006)

Notes: Average allocative efficiency for the last bid that subjects placed in each match. Unit of observation is a group of three subjects. Bootstrapped standard errors are in parentheses. $>$, $\gg$, and $\ggg$ denote significance at 0.10, 0.05, and 0.01 levels, respectively. p-values are determined using two-tailed permutation tests [Good, 2013].

Table 3.5 shows that allocative efficiency is significantly higher when the costs are $C = 0.1$. This result provides support to Hypothesis 1 and leads to the conclusion that frictions in the GSP market can help improve efficiency and therefore the overall social welfare.

Exploratory Behavior

Table 3.6 presents the number of bid adjustments observed across the treatments of our experiment in matches 5-10. The table is split into three panels based on the rank of the private value of the participant similar to the simulation results in Section 3.3.3. That is, the participant with the highest private value among the three is labeled as the highest-valued, the participant with the second-highest private value among the three is labeled as medium-valued, and the participant with the lowest private value among the three is labeled as lowest-valued. The columns within each panel vary the costs of bid adjustments. The rows vary the similarity of the two slots that are auctioned off.

Table 3.6.: Subject Bid Adjustments

	(a) Highest-valued			(b) Medium-valued			(c) Lowest-valued		
	$C = 0.0$		$C = 0.1$	$C = 0.0$		$C = 0.1$	$C = 0.0$		$C = 0.1$
$\alpha = 0.2$	31.125 (5.002)	$\overset{0.0}{\ggg}$	3.438 (0.76)	51.292 (5.324)	$\overset{0.0}{\ggg}$	3.458 (0.454)	65.583 (8.988)	$\overset{0.0}{\ggg}$	3.083 (0.525)
	$\sim$ 0.657		$\sim$ 0.45	$>$ 0.084		$\sim$ 0.599	$\sim$ 0.204		$\sim$ 0.583
$\alpha = 0.5$	34.167 (4.238)	$\overset{0.0}{\ggg}$	2.667 (0.279)	38.646 (4.77)	$\overset{0.0}{\ggg}$	3.125 (0.359)	51.583 (6.065)	$\overset{0.0}{\ggg}$	2.708 (0.349)
	$\sim$ 0.74		$\gg$ 0.044	$>$ 0.053		$\sim$ 0.287	$\sim$ 0.938		$\sim$ 0.346
$\alpha = 0.8$	36.857 (6.744)	$\overset{0.0}{\ggg}$	1.929 (0.221)	26.69 (3.372)	$\overset{0.0}{\ggg}$	2.571 (0.329)	52.333 (6.996)	$\overset{0.0}{\ggg}$	4.024 (1.222)
	$\sim$ 0.503		$\ll$ 0.029	$\lll$ 0.0		$\sim$ 0.135	$\sim$ 0.266		$\sim$ 0.536
$\alpha = 0.2$	31.125 (5.074)		3.438 (0.745)	51.292 (5.299)		3.458 (0.447)	65.583 (8.985)		3.083 (0.52)
Average:	33.928 (3.076)	$\overset{0.0}{\ggg}$	2.71 (0.29)	39.406 (2.793)	$\overset{0.0}{\ggg}$	3.072 (0.224)	56.681 (4.37)	$\overset{0.0}{\ggg}$	3.239 (0.435)

Notes: **Panel (a)** presents the average number of bid adjustments made by the highest-valued participants in each group. **Panel (b)** presents the average number of bid adjustments made by the medium-valued participants in each group. **Panel (c)** presents the average number of bid adjustments made by the lowest-valued participants in each group. The unit of observation is a subject per match. Bootstrapped standard errors are in parentheses. $>$, $\gg$, and $\ggg$ denote significance at 0.10, 0.05, and 0.01 levels, respectively. p-values are determined using two-tailed permutation tests [Good, 2013].

We find that the number of bid adjustments in the $C = 0.0$ treatment is an order of magnitude larger than in the $C = 0.1$ treatment. Thus, we find support for Hypothesis 2, namely, that lower costs lead to more exploration in the GSP auction.

Bid-to-Value Ratios

Table 3.7 presents the bid-to-value ratios observed in the experiment. We find three main results from Table 3.7. First, comparing panels (a), (b), and (c), we find that the lowest-valued participants substantially overbid compared with the others. This finding validates Hypothesis 3. Second, by comparing columns $C = 0.0$ and $C = 0.1$ from panel (c) we find that the bid-to-value ratio for the lowest-valued participants is higher when frictions are absent. This finding validates Hypothesis 4. Finally, for the bid-to-value ratios across the different values of α, we find partial support for Hypothesis 5. In particular, for two (out of six) cases, the bid-to-value ratios for $\alpha = 0.2$ are significantly higher than for $\alpha = 0.8$, which is consistent with Hypothesis 5; however, for the other four cases, the differences are not significant.

Table 3.7.: Subject Bid-to-Value Ratios

	(a) Highest-valued			(b) Medium-valued			(c) Lowest-valued		
	$C = 0.0$		$C = 0.1$	$C = 0.0$		$C = 0.1$	$C = 0.0$		$C = 0.1$
$\alpha = 0.2$	0.952 (0.032)	$\overset{0.209}{\sim}$	0.901 (0.025)	0.951 (0.037)	$\overset{0.453}{\sim}$	0.913 (0.031)	2.826 (0.377)	$\overset{0.003}{\ggg}$	1.668 (0.191)
	$\gg^{0.018}$		$\gg^{0.011}$	$\sim^{0.605}$		$\sim^{0.285}$	$\sim^{0.372}$		$\sim^{0.194}$
$\alpha = 0.5$	0.839 (0.033)	$\overset{0.316}{\sim}$	0.793 (0.032)	0.92 (0.044)	$\overset{0.329}{\sim}$	0.863 (0.034)	3.815 (0.889)	$\overset{0.0}{\ggg}$	1.341 (0.155)
	$\gg^{0.041}$		$\sim^{0.209}$	$\ggg^{0.003}$		$\sim^{0.192}$	$\sim^{0.307}$		$\sim^{0.802}$
$\alpha = 0.8$	0.725 (0.044)	$\overset{0.942}{\sim}$	0.729 (0.039)	0.734 (0.045)	$\overset{0.39}{\sim}$	0.789 (0.044)	2.646 (0.61)	$\overset{0.006}{\ggg}$	1.284 (0.153)
	$\lll^{0.0}$		$\lll^{0.0}$	$\lll^{0.0}$		$\ll^{0.023}$	$\sim^{0.816}$		$\sim^{0.13}$
$\alpha = 0.2$	0.952 (0.032)		0.901 (0.024)	0.951 (0.037)		0.913 (0.031)	2.826 (0.373)		1.668 (0.185)
Average:	0.844 (0.023)	$\overset{0.283}{\sim}$	0.811 (0.019)	0.874 (0.026)	$\overset{0.635}{\sim}$	0.858 (0.021)	3.115 (0.387)	$\overset{0.0}{\ggg}$	1.438 (0.097)

Notes: **Panel (a)** presents the average bid-to-value ratio per match across subjects with the highest private value in each group. **Panel (b)** presents the average bid-to-value ratio per match across subjects with the second-highest private value in each group. **Panel (c)** presents the average bid-to-value ratio per match across subjects with the lowest private value in each group. The unit of observation is a subject per match. Bootstrapped standard errors are in parentheses. $>$, $\gg$, and $\ggg$ denote significance at 0.10, 0.05, and 0.01 levels, respectively. p-values are determined using two-tailed permutation tests [Good, 2013].

To summarize the computational and experimental results – we find that behavior by the lowest-valued participant (as captured by the number of bid adjustments and bid-to-value ratios) is key to the outcomes of the GSP. As presented in Table 3.6, in the presence of frictions, the agents seldom explore and experiment with higher bidding strategies. However, in the absence of friction costs, the exploration increases substantially. The exploratory behavior, in turn, is associated with substantial overbidding for the lowest-valued participants (as presented in Table 3.7). Such overbidding further cascades into the bids placed by the higher-valued agents, by either pushing them to increase their bids or stay put and be less likely to win the auction, which in turn may lead to an inefficient allocation (as presented in Table 3.5).

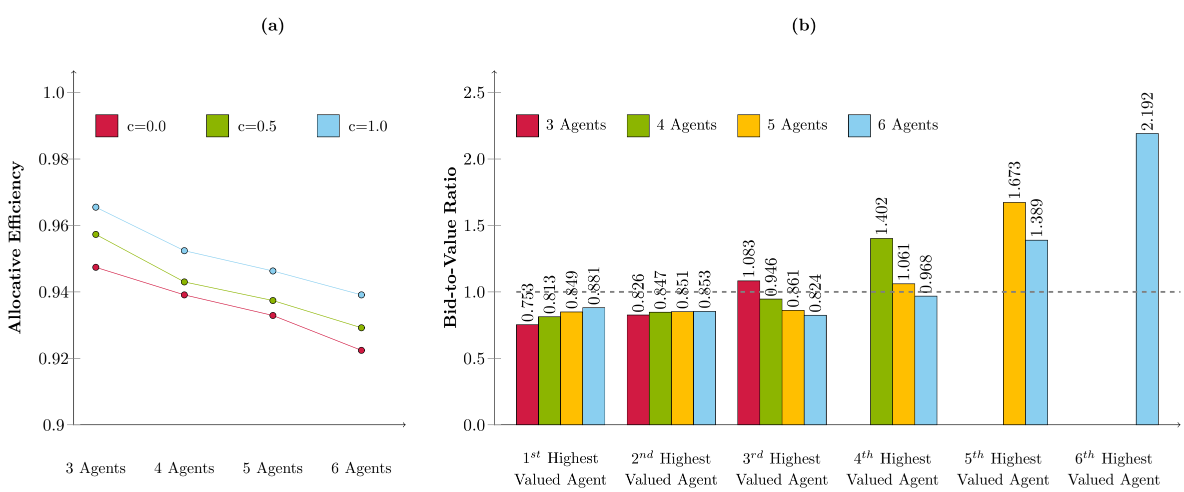
3.5.2 Additional Insights

Given that our computational model was successful at qualitatively predicting the outcomes from the human-subject experiments, we now extend it to scenarios that are not practical (e.g., costly) to carry out in the laboratory. In other words, we treat the computational agents as being the digital twins to the experimental agents to study several scenarios. In particular, in Section 3.5.2, we consider the effect of increased market demand on bid-to-value ratios and allocative efficiency. Then, in Section 3.5.2, we consider the effect of increased market supply on the two measures of interest.

Impact of Increasing Market Demand

What happens if the number of advertisers in the market increases? In particular, what if the entry cost is lowered and a new set of low-valued advertisers enters the market? According to Edelman, Ostrovsky, Schwarz (2007) [Edelman et al., 2007], such an increase in low-valued advertisers should not affect the bidding behavior or efficiency of the auctions, because the non-winning participants submit their values and would not win. However, as we have shown empirically, the lowest-valued advertisers are most likely to overbid. Hence, an increase in competition among the lowest-valued advertisers might further impact our auction metrics.

Figure 3.3 presents the efficiency and the bid-to-value ratios when we vary the number of advertisers from three to six. Specifically, we hold $\alpha = 0.5$, $C = 0.5$, $K = 2$, and vary $J \in \{3, 4, 5, 6\}$. Crucially, in the simulations, we have retained the same valuation for the top two advertisers. That is, additional agents had valuations at most as the second-highest advertiser. In the figure, the bid-to-value ratio of agents is grouped by the rank of the advertiser. The colors across the groups corresponds to a specific scenario; for example, the red bar corresponds to having three agents in the marketplace, and the blue bars correspond to having six agents in the marketplace.



Note: (a) Allocative efficiency. (b) Bid-to-value ratios. The simulation results are for $\alpha = 0.5$,and $K = 2$ ad-slots. Private values of the first- and second highest-valued agents are held the same. Private values for the remaining agents are restricted to be at most the value of the second highest-valued agent. For the bid-to-value ratio simulation, the bid-adjustment cost is set to $C = 0.5$

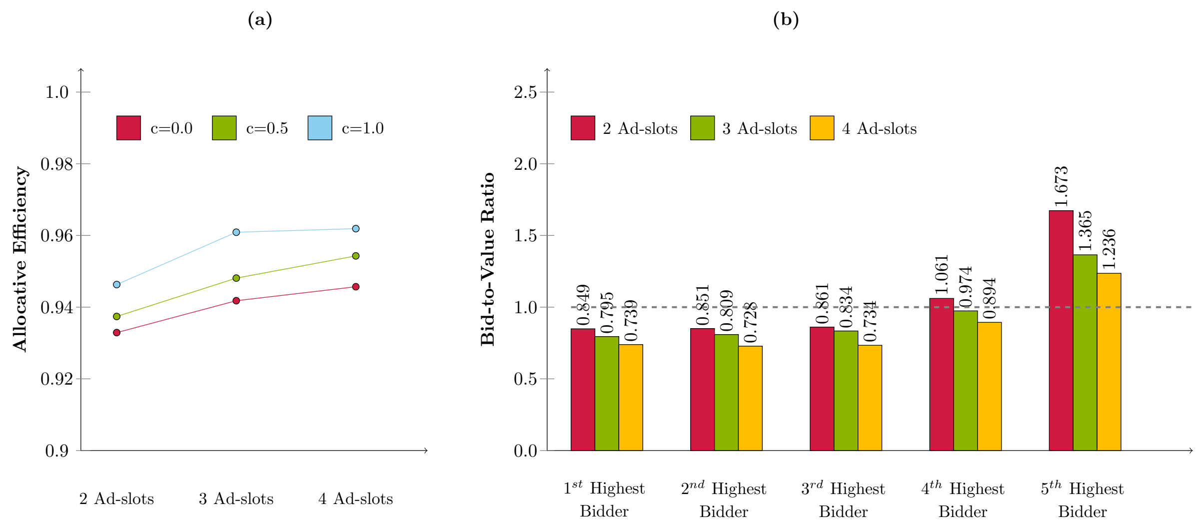
Figure 3.3.: Increasing Number of Advertisers

Several observations from Figure 3.3 are worth noting. First, panel (a) shows that as the number of advertisers increases, the efficiency of the auction decreases. Second, panel

(b) shows that the lowest-valued agents overbid. Furthermore, as the number of agents increases, the amount of overbidding by the lower-valued players also increases. Finally, panel (b) shows that there are cascading price increases across the entire cohort; that is, the lowest-valued advertiser increases the bid by the second-lowest valued advertiser and so on. So, if we focus on the "1st highest-valued agent," we find that the bid-to-value ratio increases from 0.753 to 0.881, when the number of advertisers increases. Importantly, these changes are not consistent with the theory in Edelman, Ostrovsky, Schwarz (2007) [Edelman et al., 2007]. Not surprisingly, the main result of our paper —allocative efficiency increasing with an increase in friction costs— holds across different market sizes.

Impact of Increasing Market Supply

What happens if the number of ad-slots available increases? To answer this question, we fix the number of agents at $N = 5$ and vary the number of slots $K \in \{2, 3, 4\}$. To proceed with this exercise, we need to make an additional assumption regarding the similarity of new ad-slots. Specifically, we assume that the value of α changes exponentially with the number of slots. For example, when 3 slots are available, we have $\alpha_1 = 1$, $\alpha_2 = \alpha$, and $\alpha_3 = \alpha^2$. Figure 3.4 presents the results. Each color in the figure corresponds to the number of auctioned ad slots. Figure 3.4 shows that as the number of slots increases, efficiency goes up, and the bid-to-value ratio of the lowest-valued advertizers goes down.



Note: (a) Allocative efficiency, (b) Bid-to-value ratios. The simulation results correspond to α = 0.5 and $N = 5$ agents. The simulation results correspond to $\alpha = 0.5$. For the bid-to-value ratio simulation, the bid-adjustment cost is set to $C = 0.5$

Figure 3.4.: Increasing Number of Ad Slots

To summarize, the additional analyses provide valuable insights regarding the allocative efficiency of the GSP auction across a number of market scenarios. In particular, we find that an increase in market demand (i.e., increase in the number of advertisers) exacerbates the problem of excessive exploration by the lowest-valued players, leading the market to less efficient outcomes. Therefore, increasing the supply of ad slots by the platform possibly resolves this issue, even if the extra slots are not of high value. However, across all the scenarios, we find that friction costs play a consistent role in determining allocative efficiency of the GSP auction. Specifically, allocative efficiency with costs is generally higher than without costs.

3.6 Conclusion

In this research, we investigate the role frictions for GSP outcomes. First, we computationally replicate the GSP environment and obtain predictions pertaining to bidding behavior and auction efficiency. We further test these predictions using an economic experiment with human subjects. We find significant overbidding by the lowest-valued advertisers, and that the presence of friction costs moderates this overbidding. In particular, subjects with the lowest private valuations are the most likely to explore their bidding strategies and learn about the behavior of other agents. This exploration leads the lowest-valued player to overbid, contradicting the assumption made in the theory of GSP. We find that the absence of friction costs leads to excessive experimentation, which hinders the market's ability to discover the optimal allocation.

From a slightly broader perspective, we make three key contributions. First, we demonstrate systematically using both the computational and the experimental model, that the problem of reducing frictions through algorithms does not necessarily translate into improving social welfare. As machine learning and AI become more prevalent, we should be cognizant of the impact of reducing frictions. The second key contribution that we wish to highlight is the use of machine-learning agents to create digital twins – a concept quite prevalent in the industry – to develop some actionable insights. We are unaware of any prior work in the IS area that has demonstrated the similarity in behaviors between computational and experimental agents. Third, we wish to highlight that the use of computational agents to develop hypotheses as another distinctive feature of our paper.

Our research is not without limitations. In particular, we considered a simplified version of the GSP in which the rank is determined solely by the advertiser's bid. In recent years, however, sponsored-search-advertising platforms have started to include other factors (e.g., ad quality, advertiser's history, etc.) to determine rank of the bid. Future research could incorporate these factors and ranking methods to understand the properties of the new auction mechanisms. The second limitation is that in this paper we have assumed all advertisers face the same cost for bid adjustments. In practice, however, there is vast heterogeneity among advertisers in terms of costs they incur, both for participating in the market and for making bid adjustments. Finally, in our research we focused on the scenario in which agents bid directly. Future research could extend our work to scenarios in which agents choose among a set of AI tools that would make bids for them. In particular, it will be important to develop mechanisms that are robust to the presence of both types of bidders in the market.

4. LEARNING, AND STATUS LOSS ON REVIEW PLATFORMS

4.1 Introduction

In the recent years, user-generated content has evolved to be the primary source of information to consumers. Yelp, a leading user-generated review platform for businesses, uses various mechanisms to incentivize users to write reviews and engage with the platform. As a part of this strategy, every year, Yelp gives status to its reviewers based on their performance on the platform, called Yelp Elite. The impact of gaining a status has been studied in various contexts in the previous literature [Lampel and Bhalla, 2007]. Although the participants seek status through pertinent efforts, they are sensitive to the idea of losing it [Pettit et al., 2010]. In this research we particularly focus on reviewers who lose their status on Yelp, and the impact this loss has on the user behavior. We further deliberate on how this change at the individual status level affects the platform overall.

The platform confers status to users based on their previous year's contribution to Yelp. Data shows that on an average an elite users retains status for at least 3 years. From the perspective of the platform, the decision whether to confer elite status to a new reviewer or to allow an existing elite reviewer to retain the status, is an important one because of the following reasons. First, with time, a user would contribute more and in the process would learn to write better reviews [Jin et al., 2018]. Having a status and losing it may moderate their future behaviour on the platform [Deodhar et al., 2019]. Moreover, status gives them an additional motivation to contribute to their peers [Huberman et al., 2004, Levina and Arriaga, 2014]. Secondly, if status is in fact affecting the learning process on the platform, the platform could reconsider designing strategic incentives to the reviewers. Lastly, with increasing online participation on platforms, status becomes more exclusive with time and if so, then the trade-off between offering elite status to a new reviewer or to let an existing reviewer retain the title becomes very critical.

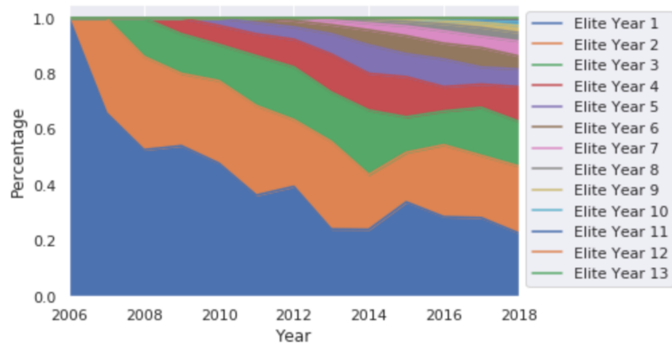


Figure 4.1.: Decreasing trend of new elite users on Yelp

In our analysis, we primarily focus on the review characteristics of the users with elite status and how losing status would impact these characteristics. We utilize Natural Language Processing (NLP) techniques from the Machine Learning literature to extract textual features and characteristics from the text of the reviews. Specifically, we perform topic modelling and sentiment analysis over the review text. Our results show that users learn multiple aspects of the review writing while they have their status. As on may expect, the loss of status leads the users to contribute less to the platform and these contributions have, on average, higher negative sentiments. However, we find that users continue to write about similar review topics that they learnt while they had the status. In other words, reviews from these users continue to follow a similar template, even after losing the status.

In addition to our preliminary analysis, we are supplement our results with the impact that status has on the user's network characteristics. Having status brings the elite reviewers to higher centrality. However, the same may not be true when they lose status. Moreover, we study this from the perspective of diversity and conformity among the type of businesses as well. Taken together, this analysis will have implications for the platform in terms of designing incentives around their status program. Next, we briefly discuss the relevant literature to our context in section 4.2 , elaborate our data and empirical strategy in section 4.3, present our results in section 4.4, and summarize our findings in section 4.5

4.2 Relevant literature

User-generated content and online word-of-mouth have been extensively studied in IS literature ([Chevalier and Mayzlin, 2006, Shen et al., 2015, Zhu and Zhang, 2010]. Chevalier et al (2006) [Chevalier and Mayzlin, 2006] demonstrate the direct impact of online reviews on economic outcomes. Various studies have looked into the development and evolution of reviews [Godes and Silva, 2012, Li and Hitt, 2008]). While online word of mouth is predominantly voluntary contribution by the users, Khern-am-nuai (2018) [Khern-am nuai et al., 2018a] demonstrate the role of financial incentives in influencing the revenue generation process. Other platforms have used intrinsic social norms [Burtch et al., 2018] or creating social networks [Goes et al., 2014]. Moreover, status gives them an additional motivation to contribute to their peers [Huberman et al., 2004, Levina and Arriaga, 2014]. Our research further contributes to this growing stream of research on online word-of-mouth and user generated content. While various incentive structures affect the process of writing reviews, reputation and status have been cited as a prominent reason in previous literature [Jin et al., 2018, Shen et al., 2015]. While the impact of losing status has been studied in other contexts [Deodhar et al., 2019], less is known in the context of online review platforms. We aim to fill this research gap by studying the immediate and long term effects of gaining and losing status on such platforms.

The basic idea is to test whether the writing quality of a review changes after a person is demoted from Elite status. There are couple of ways to posit this. One way could be that once a reviewer becomes Elite, any review she writes comes from the same template that she has perfected over the past reviews. Another way of saying the same idea would be to say that once a reviewer learns how to write a 'useful' review, she cannot unlearn it. If any of this hypothesis is true, then the usefulness of a review should not get affected even if a reviewer loses status. On the methods front, we employ state of the art machine learning tools for Natural Language Processing, including sentiment analysis [Schumaker et al., 2016] and topic modelling [Lee et al., 2018].

4.3 Empirical Setup

4.3.1 Data

Yelp provides researchers with an academic dataset, which contains reviews and information for different business unit from 11 cities between 2006 and 2018. The data has over 6 million reviews written by 1.2 million users for 192,609 businesses in total. Out of these users, 63,385 of them have been conferred with the elite status at some point of time. Potentially users can write reviews in other cities as well. Therefore to confine our analysis to local reviews we only consider the set of users who have at least 80% of their reviews written in the available dataset. In our analysis, we consider 399 elite users who have had status for 3 continuous years (for tractability) and do not regain it. As we are interested in the impact of losing status, we aggregate and reset the timeline of reviews for these users using the definition of time as described below in Table 4.1.

Table 4.1.: Aggregated Elites as per the year of gaining status

year 0: *no status*	User doesn't have a status. (Baseline for performance)
year 1: *gaining status*	User contributes to get the status.
year 2: *gains status*	User gains status and continues to participate on the platform.
year 3: *has status*	User maintains the status and participation
year 4: *losing status*	User doesn't have a status.
year 5: *lost status*	User loses status

Using this definition of aggregated years, all the data is aggregated into a panel at user-year level. Figure 4.2 visualizes the average rating and number of reviews written by each user. We can notice that year 2 (when the user gains the status), sees a substantial increase in participation from the user. At the same time, the variance in the rating decreases.

On the other hand, during year 5 (when status is lost), there is lower participation and higher variance in rating. However, these two variables do not sufficiently describe the reviewer behaviour. Therefore, we utilize Natural Language Processing (NLP) techniques from the advancing machine learning literature to extract features with greater details. More specifically, we extract text sentiment scores [Pang et al., 2008] and review topics using Latent Dirichlet Allocation (LDA) [Blei et al., 2003]. We heuristically select 5 major topics from the reviews. Evaluating the semantics of these topics, we know that topic 1 corresponds to service times, topic 2 corresponds to the ambience of the place, topic 3 corresponds staff and services, topic 4 corresponds to friends and recommendations, and topic 5 corresponds to description of food. Further, we also consider the review length and compliments (funny,cool and useful) the user receives for the reviews. Summary statistics for all the variables are presented in Table 4.2.

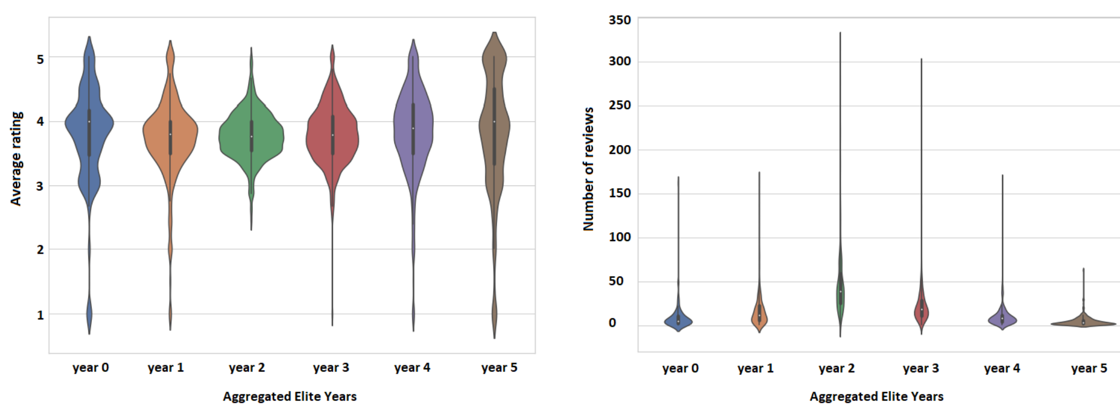


Figure 4.2.: Distributions of review characteristics across aggregated years

Although, we have utilized traditional NLP techniques to extract some features from text of the reviews, there are newer tools and techniques to extract informative features. Firstly, we measure quality by measuring writing quality, in terms of grammar quality of the reviews. The overall quality of the review is reflected by 4 measures in our setting; a) Readability Scor, b) Gunning fox Index, c) Automatic Reading Index, and d) Lexical density. We define these measure in detail in the later sections. Secondly, we uniquely calculate informativeness

Table 4.2.: Summary Statistics of the variables of interest

Variable	Mean	Std Dev.	Minimum	Maximum
Number of Reviews	21.66	28.04	1	319
Average Star Rating	3.79	0.67	1	5
Review Length	939.689	548.35	97	4,988
Compliments	1.695	1.746	0	20
sentiment compound	0.772	0.256	-0.968	0.999
sentiment negative	0.041	0.022	0.000	0.217
sentiment neutral	0.774	0.053	0.408	1.000
sentiment positive	0.185	0.056	0.000	0.592
topic 1	0.179	0.106	0	1
topic 2	0.156	0.122	0	1
topic 3	0.189	0.121	0	1
topic 4	0.232	0.152	0	1
topic 5	0.198	0.122	0	1

of a review is to calculate the ratio of number of unique entities in the review to the total number of unique entities observed in all the reviews for that restaurant. For example, there may be many aspects of a restaurant that are spoken about in the reviews. An elite reviewers is known to address most of the aspects of the restaurant in their experiences and make them more informative. This measure has to be calculated specific to the restaurant. In doing so, we assume that the overall aspects/entities of a restaurant remain constant over time.

For our analysis, although we have utilized data from academic dataset, we run into a missing data problem. The dataset only has data for reviews written by the focal users in 11 cities. In terms of users, the dataset only has details about the reviews written by these users in these 11 cities. However, reviewers also travel and a substantial portion of them write reviews in other locations of their travel. Therefore, utilizing the unique user id information from our data, we have programmed a web crawler that collects additional data for each user. This additional data includes all the reviewers written by the focal users beyond the cities covered in our data. We augment our existing dataset with all this additional data and utilize it for our main analysis.

4.3.2 Methodology

Our empirical strategy involves infrence from two models (4.1 and 4.2). Recall that there is a delay in granting of status on Yelp, as the users are reviewed at the end of the year for status in upcoming year. Therefore, we consider only years 0, 3 and 5 for our analysis. We exclude year 1 because, some users may consciously work towards gaining the status and we cannot mitigate the self selection in that regard. Year 2 is when the user gains the status for the first time and there may be some immediate effects of status on his status, and therefore we also exclude it. Note that year 0 relates to having no status, year 3 relates to already having the status and year 5 relates to having lost the status. We are interested in the impact of losing status on user review characteristics. Some of these features may only be relevant/significant while having status. Therefore, for our empirical analysis, we consider the following two models in tandem:

$$DV_{it} = \gamma_0 * no\_status + \gamma_1 * has\_status + \gamma_2 * lost\_status + \alpha_i + \epsilon_{it}. \tag{4.1}$$

$$DV_{it} = \gamma_1 * has\_status + \gamma_2 * lost\_status + \alpha_i + \epsilon_{it}. \tag{4.2}$$

where DV_{it} is the variable of interest for user i in time (aggregated year) t, variables *no_status, has_status* and *lost_status* are indicator variables corresponding to years 0, 3 and 5 respectively, and α_i corresponds to the user fixed effects. Therefore, in Model 4.1 *no_status* will be the baseline and in Model 4.2, *has_status* will be the baseline. Currently, our analysis only estimates the difference between having status and losing status for various characteristics of the user. However, this change may be driven by a platform level changes and may not be specific to the users with status. Therefore, for analysis, we propose to build a Diff-in-diff by matching treatment group of users with a control group of users who do not lose status. This will also help us conduct various robustness checks in accordance with the assumptions of a causal model.

The interpretation of the models is as follows. If *has_status* and *lost_status* are statistically significant in results for Model 4.1, and we find no significant evidence for *lost_status* in Model 4.2, then the users are updating their behavior while in status and continue to exhibit it even after losing the status. Alternatively, if *lost_status* is not significant in Model 4.1, then any effect observed while having status is lost after the status is lost. We present our main results in section 4.4.

4.4 Results

As described above, in our causal analysis, we consider year 0, year 3, and year 5. We specifically look at two sets of variables. The first set of variables correspond to direct observable review characteristics viz., number of reviews, average star rating, review length, and amount of compliments received. The second set of variables that we consider are machine generated, which include the topic scores, sentiment scores, and review quality metrics. It is important to segregate these two categories for the following reasons. Firstly, the observable characteristics are biased [Yin et al., 2016]. These characteristics involve subjective evaluation of how the consumer perceives the review experience. On the other hand, the second set of variables are machine generated and are objective measures of quality of data. Secondly, the consumer perception of having a status or not does not affect the machine generated characteristics, while it can directly influence the user giving compliments. In this section, we present the results for first set of variables in table 4.3, and the second set of variable in table 4.5 and 4.4.

From table 4.3, we observe that users exhibit higher participation on the platform, while we observe no change in the average of their rating distribution. Moreover, they write longer reviews and gain compliments for their reviews only while they have their status active. The results on column (4), corresponds to overall compliments received by the focal users. As the users gain status, the human perception of the quality of reviews is improving. This effect disappears once the users lose status. There may be multiple reasons for this observation. It

Table 4.3.: Results using Review Characteristics

Dep. Variable:	(1) average rating	(2) number of reviews	(3) review length	(4) compliments
	Model 1			
no_status (baseline)	3.77***	10.05***	821.55***	1.41***
	(0.07)	(2.26)	(59.39)	(0.21)
has_status	0.02	15.16***	186.70***	0.56**
	(0.08)	(2.51)	(65.83)	(0.23)
lost_status	0.02	-5.05*	100.27	0.32
	(0.09)	(2.70)	(70.90)	(0.25)
	Model 2			
has_status (baseline)	3.80***	25.22***	1008.24***	1.97***
	(0.03)	(1.10)	(28.54)	(0.10)
lost_status	-0.00	-20.21***	-86.43*	-0.23
	(0.06)	(1.86)	(48.27)	(0.17)
User Fixed Effect	Yes	Yes	Yes	Yes

* $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

could be that the users start writing low quality reviews and the consumer react accordingly. Conversely, the quality of the review is unaffected, but the consumer perception of the review reduces, as the status is lost. Therefore, it is important to look at the second set of variable around machine based features, which will help us understand the mechanism better.

Table 4.4.: Results from Review Sentiments

Dep. Variable:	(1) compound	(2) negative	(3) neutral	(4) positive
	Model 1			
no_status (baseline)	0.767***	0.038***	0.760***	0.201***
	(0.028)	(0.002)	(0.006)	(0.006)
has_status	0.021	0.002	0.021***	-0.023***
	(0.031)	(0.003)	(0.006)	(0.007)
lost_status	-0.026	0.005*	0.014*	-0.018**
	(0.033)	(0.003)	(0.007)	(0.007)
	Model 2			
has_status (baseline)	0.788***	0.041***	0.781***	0.178***
	(0.013)	(0.001)	(0.003)	(0.003)
lost_status	-0.047**	0.002	-0.008*	0.005
	(0.021)	(0.002)	(0.004)	(0.005)
User Fixed Effect	Yes	Yes	Yes	Yes

* $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

Interestingly, from Table 4.4, we find that the users write higher amount of negative references and a lower amount of positive references in their reviews, after losing status. The compounded sentiment significantly reduces after losing the status. This suggests that the users post reviews motivated by relatively negative experiences after losing the status. From Table 4.5, we find that users significantly reduce writing about ambience (topic 2) and food (topic 5), while they highlight mentions of friends and their recommendations (topic 4) in the reviews. More interestingly, these users continue this review writing behavior after losing the status as well. Therefore, elite users learn to write reviews by selectively including/excluding some topics and they continue to exhibit this learning even after losing their status. Taking these observation together with the results in table 4.3, we can conclude that the users learn write a wider range of topics while they have status, and their sentiments change when they subsequently lose it. This results in other consumers not perceiving the reviews to be of higher quality. Therefore, consumer perception is driven by status, in this case. This further leads to interesting insights for the platform manager. There is a negative externality to the platform when existing elite reviewers are demoted. Therefore, platforms need to reconsider their process of reassigning the status, keeping the overall quality of content on the platform in perspective.

4.5 Discussion and Conclusion

User-generated content platform are now ubiquitous. Consumers heavily rely on such information from their peers while making consumption decisions. Such platforms need to balance the trade off between high quality content and consumer engagement. Yelp, a online review platform, heavily relies on their gamification practices to incentivize user contributions, the most popular being Elite status. While literature has focused on the impact of gaining status on user=generated content platforms, less is known about the impact of such users losing status to the platform.

Table 4.5.: Results from Review topics

Dep. Variable:	(1) topic 1	(2) topic 2	(3) topic 3	(4) topic 4	(5) topic 5
			Model 1		
no_status (baseline)	0.168***	0.195***	0.194***	0.190***	0.215***
	(0.011)	(0.013)	(0.013)	(0.017)	(0.013)
has_status	0.018	-0.041***	-0.007	0.050***	-0.024*
	(0.013)	(0.014)	(0.014)	(0.019)	(0.015)
lost_status	0.011	-0.050***	-0.015	0.051**	-0.006
	(0.014)	(0.016)	(0.015)	(0.020)	(0.016)
			Model 2		
has_status (baseline)	0.186***	0.154***	0.186***	0.240***	0.191***
	(0.005)	(0.006)	(0.006)	(0.008)	(0.006)
lost_status	-0.007	-0.009	-0.007	0.001	0.017*
	(0.009)	(0.010)	(0.010)	(0.014)	(0.010)
User Fixed Effect	Yes	Yes	Yes	Yes	

* $p < 0.1$; ** $p < 0.05$; and ***$p < 0.01$.

In this research, we are focused on the long term evolution of review writing. More specifically, we are interested in how reviewers learn to write reviews over time, with respect to things they include in the review as well as the format of the review itself. This effect might be dependent on various other heterogeneous factors like the deviation from the overall experience with the precedent set from review until then, etc. Our work is evidence of the impact that losing status has on reviewers on a user generated content platform. From the platform manager's perspective, this poses an interesting question: "Does demoting an existing reviewer hurt the platform?". While platforms strive to not distribute status to everyone and maintain exclusivity, there is a tradeoff between converting new users to elite status versus continuing existing users to have the status.

Our research is preliminary and not without limitations.There may be endogeneity concerns that may arise due to self-selection by the users. In addition, we are extending our work by including the impact that losing status has on the user networks, and the implications that would have for businesses on the platform. Moreover, conformity and diversity of the reviews may also be affected due to loss of status. Understanding the impact form all these dimensions will help in developing meaningful insights for the platform, in terms of designing incentives around the status program.

5. CONCLUSIONS & FUTURE WORK

In this dissertation, I focus on analyzing design artifacts in three different contexts of platforms-based markets. The first essay studies the impact of augmented-reality app based incentives on real-world businesses. By studying the impact of Pokémon Go on local businesses, we establish that there is higher consumer engagement and more positive consumer perception for the business that are associated with the in-game artifacts. In addition, the effect on consumer perception is not significantly different among diverse restaurant while the effect on consumer engagement varies. We observe that business characteristics like pricerange of the restaurant, popularity and the neighborhood significantly moderate this impact. Moreover, we also study the heterogeneity among the reviewers that these businesses attract. We find that the game has attracted significant number of new users to the restaurants. These users tend to be predominantly local users. We also conduct several diagnostic tests to establish the robustness of our results. This research provides empirical evidence of the economic impact of augmented reality applications. These results, particularly the heterogeneous effects, help the business managers in developing appropriate policies for governing any partnership between their businesses and such augmented-reality applications.

In the second essay we investigate the role played by reduced market frictions in sponsored search ad markets. First, we computationally replicate the Generalized second price auction environment and obtain predictions pertaining to bidding behavior and auction efficiency. These predictions are further tested using a human-subject experiment. The main result of this work is that we find significant overbidding by lower valued advertisers in the market. This leads to inefficient allocations in the markets.Owing to the complex nature of online ad ecosystem, understanding the impact of reducing frictions can help the policymakers to regulate this market characteristic and achieve higher market surplus overall. Further, this study explores the tradeoff between market efficiency and revenues, as resulted from changing market environment and dynamics.

The third essay studies the impact of status on a user-generated content platform. We utilize data from a Yelp academic dataset for this purpose. To extract the relevant features from review text, we utilize state of the art Natural Language processing techniques. Specifically, we perform sentiment analysis and topic modeling on the review texts. As platforms grow, it is important for the manager to maintain incentives for the user to contribute while not compromising on the overall content quality on the platform. Platforms like Yelp significantly utilize gamification practices to incentivize user contribution, Elite status being the most prominent. On the one hand, status leads to exclusivity and incentivizes higher quality contributions. Such an updated behaviour may or may not hold in the long term, especially when the status is lost. Our preliminary results show that users learn multiple aspects of the review writing process in order to gain status. while losing status does have an impact on the amount of contributions made by the user, the nature of change in reviews is important to understand. We observe that the users continue to writing reviews following a template that they have learnt in terms of topics. Moreover, while the machine perceived quality measures significantly reduce, the human perception of status continues to have a positive impact even after the loss of status. We conclude with policy recommendations to the platform on how to manage status and incentives in the long run, especially on platforms with large engagement. We further discuss the impact of losing status on conformity and diversity of the review generation process. Understanding the impact form all these dimensions will help in developing meaningful insights for the platform, in terms of designing incentives around the such status program.

In conclusion, this dissertation focuses on studying user engagement on online platforms. We employ a variety of methodologies including difference-in-difference, propensity score matching, panel data models, natural language processing, reinforcement learning and human subject experiments to aid us in answers our research questions. We provide insights for a platform on how interaction with design artifacts significantly impacts the outcomes for the platform as well as the market. As user generated content platforms continue to grow, these insights provide managers with a framework for developing a policy on designing incentives that lead to optimal outcomes for the platform.

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A. APPENDIX

A.1 Additional Details about Q-learning for GSP

In this section, we elaborate the details of Q-learning implementation for GSP. In particular, Q-learning [Watkins and Dayan, 1992] is a Markov Decision Process (MDP), where agents learn an optimal (action selection) policy that maximizes the expected value of their overall reward. In other words, it is an advanced stochastic learning process. The learning happens through repeated interactions with the environment over time. For example, suppose that at time t agent is in state s_t and selects an action $a \in A(s_t)$. Furthermore, suppose that an agent observes a reward π_t and transitions to the state s_{t+1}, then the agent updates their value ($Q(s_t, a)$) of being in state s_t and taking an action a through a simple convex combination of the old value and the new value (i.e., value of the reward plus the value of being in the new state), as follows:

$$Q^{new}(s_t, a) \leftarrow (1-\delta)\, Q(s_t, a) + \delta\, (\pi_t + \gamma\, max_{a' \in A(s_{t+1})}\, Q(s_{t+1}, a')), \tag{A.1}$$

where $0 \leq \delta \leq 1$ is the learning rate and $0 \leq \gamma \leq 1$ is the discount factor.

The actions are chosen stochastically in such a way that better actions (i.e., those that have higher Q-values) are chosen more often. A common implementation of the action-section policy is through the use of the Boltzmann function (also known as the *softmax* policy). Algorithm 1 presents the pseudo code for implementing Q-learning in the context of GSP.

Initialize $Q(s,a)$ for all state-action pairs (s,a) for $J = 3$ agents. The state, s, is a tuple of private value and previous bid (v^j, b^j_{t-1}), and the action, a, is a possible bid $b \in \{0.0, 1.0, ..., 9.0, 10.0\}$

for $N \leq 1000$ *iterations* **do**

  for $M \leq 2000$ *matches* **do**

    Assign private values $V^j \in \mathrm{U}\{1, 10\}$ for all J agents

    for $t \leq 100$ *time periods* **do**

      For each agent j

      1. Draw a bid $a^j_t \in U\{0, 10\}$ using *Boltzmann softmax* policy over $Q(s^j_t)$
      2. Observe reward, $\pi^{(k)}_t = \alpha_k(v^{(k)}_t - b^{(k+1)}_t) - C^{(k)}$, and next state, s^j_{t+1}
      3. Update $Q^{new}(s_t, a_t) \leftarrow (1 - \delta)\ Q(s_t, a_t) + \delta\ (\pi_t + \gamma\ max_a\ Q(s_{t+1}, a))$

    end

    Record the auction outcomes

  end

  Repeat with the same values of for V

end

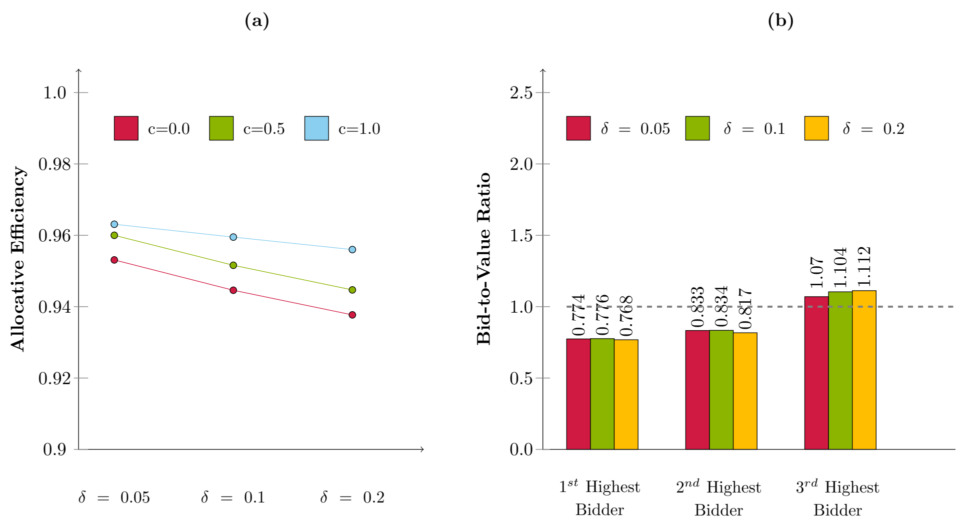
Algorithm 1: Pseudo code for the Q-learning algorithm

The learning simulations are run for $M = 2000$ matches, each with $t = 100$ periods. Once the agents submit their bids at period t, the auctioneer ranks them and reports the allotted slot as well as the clearing price for each agent. Since there are $K = 2$ slots, only two agents receive allocations. The agents update their Q-value function at the end of each period t and auction observations are recorded at $t = 100$ (i.e., at the end of each match). For each match, we record private value V^j, final period bid b^j_{100} and number of bid updates made by each player during the match. Using these observations, we calculate allocative efficiency (Ψ) and bid-to-value ratios (Ω^j). We execute the entire learning model for $N = 1000$ iterations. To make these iterations comparable, we retain v^j to be the same for a given match m across the iterations.

The main research questions of the paper are regarding the effect of friction costs (C) and ad slot similarity (α), therefore we varied $C \in \{0.0, 0.5, 1.0\}$ and $\alpha \in \{0.2, 0.5, 0.8\}$ in the main body of the paper. Nevertheless, there are three additional parameters (δ, γ and λ) that are part of the learning model. In particular, for the results carried out in the main body of the paper, we set $\delta = 0.1$, $\gamma = 0.99$ and $\lambda = 1$. Next, we describe these parameters in more detail and provide robustness checks on the extent to which our conclusions depend on this choice.

A.1.1 Learning rate, δ

The learning rate, δ, determines the extent to which the reward and value of being in the new state override the previously learned value. It is common practice is to use $\delta = 0.1$. To check whether predictions obtained in Section 3.3.3 of the paper are robust to the choice of δ, we vary $\delta \in \{0.05, 0.1, 0.2\}$. Figure A.1 presents the results for allocative efficiency (panel (a)) and bid-to-value ratios (panel(b)). The figure shows that the key takeaways on allocative efficiency and bid-to-value ratios are qualitatively the same, regardless of δ.

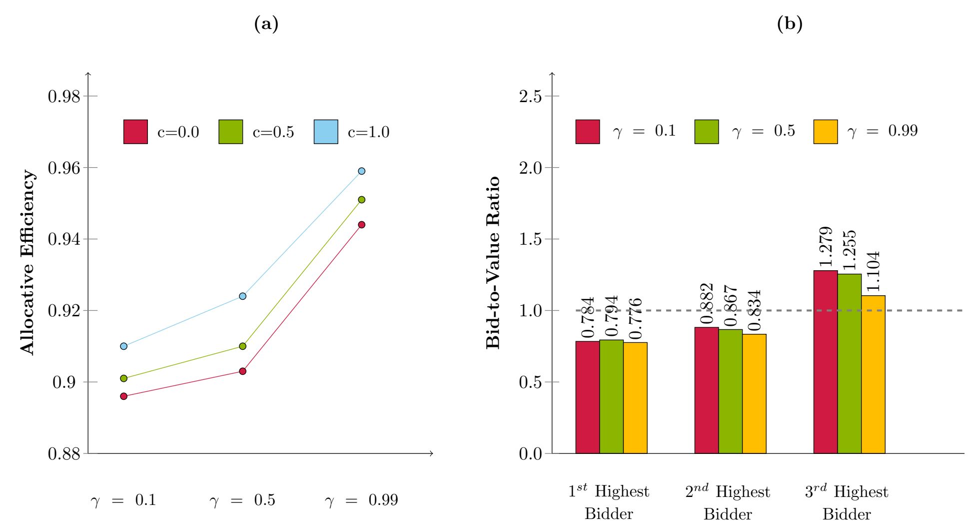


Note: (a) Allocative efficiency. (b) Bid-to-value ratios. The simulation results are for $\alpha = 0.5$, $\lambda = 1$, $\gamma = 0.99$ and $K = 2$ ad slots. For the bid-to-value ratio simulation, the bid-adjustment cost is set to $C = 0.5$.

Figure A.1.: Robustness of δ

A.1.2 Discounting factor, γ

The discounting factor, γ, determines the extent to which the agent values the immediate reward relative to the future rewards. For example, when $\gamma \to 0$, the agent is myopic, because she only considers current reward. For the simulations provided in the main body of the paper, we used $\gamma = 0.99$. This was done in order to keep the value γ the same as for human-subject experiments.[1] To further clarify that our results are *not* driven by the choice of γ, we present the robustness results for $\gamma \in \{0.1, 0.5, 0.99\}$ in Figure A.2. Notice that the impact of costs on allocative efficiency and bidding behaviour remain qualitatively consistent with our main result. The figure also shows that the problem identified in the main body of the paper is amplified as agents become more myopic.



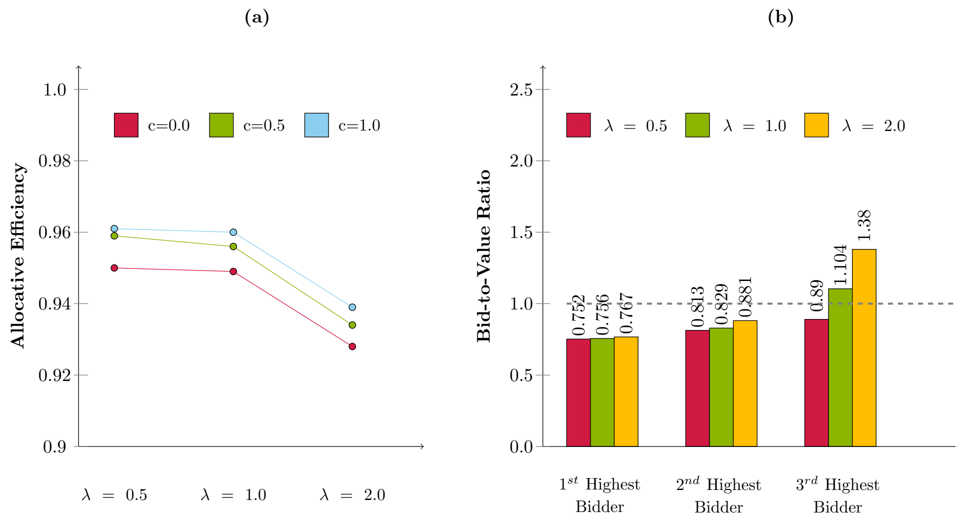
Note: (a) Allocative efficiency. (b) Bid-to-value ratios. The simulation results are for $\alpha = 0.5$, $\lambda = 1$, $\delta = 0.1$ and $K = 2$ ad-slots. For the bid-to-value ratio simulation, the bid-adjustment cost is set to $C = 0.5$.

Figure A.2.: Robustness of γ

[1] In the experiment there was a 99% chance that the match will continue to the next period and 1% probability that the match will terminate in the current period.

A.1.3 Temperature/exploration parameter, λ

The temperature parameters, λ, determines the extent to which better actions are chosen over poor actions. For example, as $\lambda \to 0$, all the actions will have equal probability of being chosen, while as $\lambda \to \infty$ the probability of the choosing the best action tends to 1. For this reason, the temperature parameters, λ, is often interpreted as the rationality parameters [e.g., Su, 2008]. In the main body of the paper, we set $\lambda = 1$. Robustness results for varying λ are presented in Figure A.3. In particular, we find the results are qualitatively consistent with our main result. However, we do find that overbidding by the third highest-valued agents is not as prevalent when λ is lower.



Note: (a) Allocative efficiency. (b) Bid-to-value ratios. The simulation results are for $\alpha = 0.5$, $\gamma = 0.99$, $\delta = 0.1$ and $K = 2$ ad-slots. For the bid-to-value ratio simulation, the bid-adjustment cost is set to $C = 0.5$.

Figure A.3.: Robustness of λ

A.2 Additional Figures and Tables

Table A.1.: Match Duration (Seconds).

Match:	1	2	3	4	5	6	7	8	9	10
Number of Seconds:	37	166	172	108	176	181	25	145	146	57

Table A.2.: Subject Bid-to-Value Ratios in Sessions 1-4

	(a) Highest-valued			(b) Medium-valued			(c) Lowest-valued		
	$C = 0.0$		$C = 0.1$	$C = 0.0$		$C = 0.1$	$C = 0.0$		$C = 0.1$
$\alpha = 0.2$	0.964 (0.04)	$\overset{0.302}{\sim}$	0.912 (0.027)	0.955 (0.05)	$\overset{0.602}{\sim}$	0.916 (0.051)	2.359 (0.331)	$\overset{0.303}{\sim}$	1.887 (0.311)
	$\gg^{0.022}$		$\gg^{0.048}$	$\sim^{0.346}$		$\sim^{0.213}$	$\sim^{0.591}$		$\sim^{0.546}$
$\alpha = 0.5$	0.83 (0.039)	$\overset{0.577}{\sim}$	0.794 (0.05)	0.876 (0.063)	$\overset{0.591}{\sim}$	0.838 (0.033)	2.606 (0.298)	$\overset{0.019}{\gg}$	1.642 (0.247)
	$\sim^{0.433}$		$\sim^{0.605}$	$\sim^{0.667}$		$\sim^{0.963}$	$\sim^{0.163}$		$\sim^{0.444}$
$\alpha = 0.8$	0.765 (0.076)	$\overset{0.933}{\sim}$	0.757 (0.047)	0.835 (0.065)	$\overset{0.946}{\sim}$	0.841 (0.055)	1.991 (0.289)	$\overset{0.113}{\sim}$	1.363 (0.232)
	$\ll^{0.019}$		$\lll^{0.006}$	$\sim^{0.15}$		$\sim^{0.337}$	$\sim^{0.431}$		$\sim^{0.217}$
$\alpha = 0.2$	0.964 (0.04)		0.912 (0.027)	0.955 (0.05)		0.916 (0.051)	2.359 (0.328)		1.887 (0.307)
Average:	0.861 (0.031)	$\overset{0.397}{\sim}$	0.827 (0.026)	0.893 (0.035)	$\overset{0.562}{\sim}$	0.867 (0.027)	2.348 (0.181)	$\overset{0.006}{\ggg}$	1.655 (0.161)

Notes: **Panel (a)** presents average bid to value ratio per match across subjects with the highest private value in each group. **Panel (b)** presents average bid to value ratio per match across subjects with the second highest private value in each group. **Panel (c)** presents average bid to value ratio per match across subjects with the lowest private value in each group. Bootstrapped standard errors are in parentheses. $>$, $\gg$, and $\ggg$ denote significance at 0.10, 0.05, and 0.01 levels, respectively. P-values are determined using two-tailed permutation tests.

Table A.3.: Subject Bid-to-Value Ratios in Sessions 5-8

	(a) Highest-valued			(b) Medium-valued			(c) Lowest-valued		
	$C = 0.0$		$C = 0.1$	$C = 0.0$		$C = 0.1$	$C = 0.0$		$C = 0.1$
$\alpha = 0.2$	0.94 (0.05)	$\overset{0.44}{\sim}$	0.889 (0.04)	0.946 (0.055)	$\overset{0.608}{\sim}$	0.91 (0.035)	3.294 (0.65)	$\overset{0.002}{\ggg}$	1.45 (0.209)
	$\wr$ 0.223		$\wr$ 0.107	$\wr$ 0.842		$\wr$ 0.756	$\wr$ 0.416		$\wr$ 0.149
$\alpha = 0.5$	0.848 (0.052)	$\overset{0.418}{\sim}$	0.793 (0.039)	0.963 (0.062)	$\overset{0.403}{\sim}$	0.888 (0.059)	5.023 (1.736)	$\overset{0.0}{\ggg}$	1.041 (0.173)
	$\vee\!\vee$ 0.049		$\wr$ 0.252	$\vee\!\vee\!\vee$ 0.001		$\wr$ 0.129	$\wr$ 0.361		$\wr$ 0.524
$\alpha = 0.8$	0.695 (0.052)	$\overset{0.864}{\sim}$	0.709 (0.058)	0.659 (0.057)	$\overset{0.298}{\sim}$	0.751 (0.065)	3.138 (1.04)	$\overset{0.031}{\gg}$	1.224 (0.208)
	$\wedge\!\wedge\!\wedge$ 0.002		$\wedge\!\wedge$ 0.02	$\wedge\!\wedge\!\wedge$ 0.0		$\wedge\!\wedge$ 0.038	$\wr$ 0.906		$\wr$ 0.474
$\alpha = 0.2$	0.94 (0.049)		0.889 (0.041)	0.946 (0.055)		0.91 (0.035)	3.294 (0.647)		1.45 (0.208)
Average:	0.828 (0.032)	$\overset{0.483}{\sim}$	0.797 (0.029)	0.856 (0.038)	$\overset{0.901}{\sim}$	0.85 (0.032)	3.818 (0.713)	$\overset{0.0}{\ggg}$	1.239 (0.114)

Notes: **Panel (a)** presents average bid to value ratio per match across subjects with the highest private value in each group. **Panel (b)** presents average bid to value ratio per match across subjects with the second highest private value in each group. **Panel (c)** presents average bid to value ratio per match across subjects with the lowest private value in each group. Bootstrapped standard errors are in parentheses. $>$, $\gg$, and $\ggg$ denote significance at 0.10, 0.05, and 0.01 levels, respectively. P-values are determined using two-tailed permutation tests.

Table A.4.: GSP Efficiency

Sessions 1–4

	$C = 0.0$		$C = 0.1$
$\alpha = 0.2$	0.936 (0.029)	$\overset{0.567}{\sim}$	0.958 (0.028)
	$\wr^{0.939}$		$\wr^{0.52}$
$\alpha = 0.5$	0.932 (0.031)	$\overset{0.15}{\sim}$	0.984 (0.009)
	$\wr^{0.327}$		$\wr^{0.259}$
$\alpha = 0.8$	0.972 (0.016)	$\overset{0.07}{<}$	0.997 (0.002)
	$\wr^{0.379}$		$\wr^{0.204}$
$\alpha = 0.2$	0.936 (0.028)		0.958 (0.027)
Average:	0.944 (0.016)	$\overset{0.083}{<}$	0.978 (0.011)

Sessions 5–8

	$C = 0.0$		$C = 0.1$
$\alpha = 0.2$	0.916 (0.031)	$\overset{0.064}{<}$	0.976 (0.009)
	$\wr^{0.78}$		$\wr^{0.188}$
$\alpha = 0.5$	0.927 (0.033)	$\overset{0.025}{\ll}$	0.99 (0.004)
	$\wr^{0.43}$		$\wr^{0.803}$
$\alpha = 0.8$	0.963 (0.022)	$\overset{0.447}{\sim}$	0.981 (0.013)
	$\wr^{0.239}$		$\wr^{0.779}$
$\alpha = 0.2$	0.916 (0.03)		0.976 (0.01)
Average:	0.935 (0.017)	$\overset{0.007}{\lll}$	0.982 (0.005)

Notes: Unit of observation is a matched group of subjects. Bootstrapped standard errors are in parentheses. $>$, $\gg$, and $\ggg$ denote significance at 0.10, 0.05, and 0.01 levels, respectively. P-values are determined using two-tailed permutation tests.

A.3 Experimental Instructions

Experiment Overview

You are about to participate in an experiment in the economics of decision-making. If you listen carefully, you could earn a large amount of money that will be paid to you in cash in private at the end of the experiment.

It is important that you remain silent and do not look at other people's work. If you have any questions, or need any assistance of any kind, please raise your hand and an experimenter will come to you. During the experiment, **do not talk, laugh or exclaim out loud**, and be sure to keep your **eyes on your screen only**. In addition, please **turn off your cell phones, etc.** and put them away. Anybody that violates these rules will be asked to leave and will **not** be paid. We expect and appreciate your cooperation.

Agenda

1. We will first go over the printed instructions.
2. After the printed instructions, there will be a set of interactive instructions on the computer that will guide you through elements of the interface.
3. After all the instructions, the experiment will begin. In the experiment, you will be working with a fictitious currency called Francs. You will be paid in US Dollars at the end of the experiment. **The exchange rate today is: 1 Franc = 0.75 USD.**

Experiment Details

- This experiment consists of **ten** matches.
- At the beginning of each match you will be **randomly matched with two other participants**. You will remain matched with these same participants until the **end of the match**, but then you will be re-matched with another two randomly selected participants for the following match.
- Each match will have the same structure, but may take different amount of time.
- You will remain **anonymous** throughout the experiment. You will not know the identity of the participant that you are matched with, and they will not know your identity.
- Your earnings in a given match is based solely on the choices made by you and the participants with whom you are matched. The choices made by you and by the participants with whom you are matched will have no effect on the earnings of participants in other groups and vice versa.

Specific Instructions for Each Match

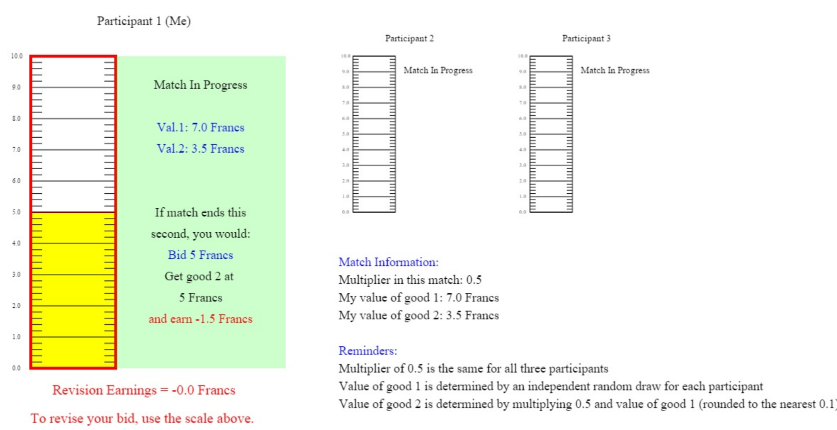
- At the beginning of each match you will be assigned a value for good 1 and a value for good 2 as follows:
  - Your value for good 1 will be drawn at random from $\{0.1, 0.2, 0.3, \ldots, 9.8, 9.9\}$ with each number equally likely.

  - Your value for good 2 will be determined by multiplying your value of good 1 and a "multiplier" which is a fraction between 0 and 1. This **multiplier will be common for all participants in your group** and fixed for the duration of each match.
  - Thus, the value of good 1 is greater than the value of good 2.

- For example, if your value for good 1 is randomly drawn to be 7.0 Francs and the multiplier is 0.5, your value for good 2 is 3.5 (=7.0*0.5). Note that all numbers are rounded to the nearest 0.1.

- **Remember, all participants in your group have the same multiplier but independently drawn values of good 1.**

- Your decision screen will be displayed like this:



- Your task will be to bid for a good using a slider on the left side of your screen.

- **You may buy only one good** - good 1 or good 2. The outcome of which good you buy depends on your bid and the bids of the participants that you are matched with as follows:
  - **If your bid is the highest** among the three bids, then
    * You will get good 1.
    * You will pay the amount equal to the second highest bid.
  - **If your bid is the second highest** among the three bids, then
    * You will get good 2.
    * You will pay the amount equal to the third highest bid.
  - **If your bid is the third highest** among the three bids, then
    * You will get neither good 1 nor good 2.
    * You will not have to pay anything.

- Note: in case of a tie ranks are determined randomly.

Additional Information about Matches

- Before every match, you will have time to review the information provided about that match.
- **When you are ready to begin** move the mouse inside the scale and wait for the match to begin.
- Mouse clicks are disabled. **You place your bid by moving the mouse** in and out of the scale rectangle on either the left of the right side.
- You will be able to **place the initial bid at no cost**.
- For the duration of the match, you will be able to make as many revisions to your bid as you want. However, the **revisions are costly**. Specifically, you will incur a **cost of 0.1 Francs per revision**.
- Current outcomes will be displayed continuously, but the outcome "that counts" is the one selected when the match ends.
- The duration of each match will not be known ahead of time. The duration of each match was determined randomly using the following procedure.
  - Each match will last at least 20 seconds. After the first 20 seconds are up, each second, a number will be chosen randomly from the set of numbers $\{1, 2, 3, \ldots, 98, 99, 100\}$, where **each number is equally likely**.
  - If the number is 1, then the match will end.
  - If the number not 1, then the match will last an additional second.
  - The number will always be placed back into the set after it is drawn.
  - Thus, after the first 20 seconds, any additional second there is a 1% CHANCE that the match will end and a 99% CHANCE that the match will continue.
  - Therefore, the expected number of seconds in each match will be 120, which means that the expected length of each match is **two minutes**.
  - You will not see the number selected from $\{1, 2, 3, \ldots, 98, 99, 100\}$.
  - To ensure that the length of the match is not dependent on your play, the number of seconds for each match has been written on the board before the experiment, and will be uncovered at the end of the experiment.
- After every match, you will have 30 seconds to review the summary for the match.

Experiment Earnings

- Your earnings in each match is equal to the value of the good that you get minus the amount that you pay for that good and minus any revision costs.
- Your earnings in each round may be positive, negative, or zero depending on your bid and the bids by the participants with whom you are matched.
- Your earnings for the experiment will be the sum of the earnings for each match plus the starting 10 Francs.

- Your cumulative earnings for the experiment (including the 10 Francs) will be displayed at the top of your screen.
- At the end of the experiment, you will be paid in **cash**.

Interactive Instructions

- At the beginning of each match, to indicate that you are ready to begin, you will need to move the mouse over the scale. The match will start when all participants are ready.
- Remember, mouse clicks are disabled throughout this experiment.

Task 1 Move your mouse over the scale on the left side of the screen.

- To set your bid you need to HORIZONTALLY MOVE the mouse outside the scale at current bid. Each bid revision will cost 0.1 Francs.

Task 2 Set your bid to $5.0.

- Information pertaining to each match will be summarized in the middle of the screen (see example below). You can review this information before you choose to start the match.
- Once you have started, you will be able to revise your bids at any moment unitl the match ends.
- Match Information (EXAMPLE)
  - Multiplier in this match: 0.5
  - My value of good 1: 7.0 Francs
  - Ma value of good 2: 3.5 Francs
- Reminders (EXAMPLE)
  - Multiplier of 0.5 is the same for all three participants
  - Value of good 1 is determined by an independent random draw for each participant
  - Value of good 2 is determined by multiplying 0.5 and value of good 1 (rounded to the nearest 0.1)

Task 3 Revise your bid to $6.0.

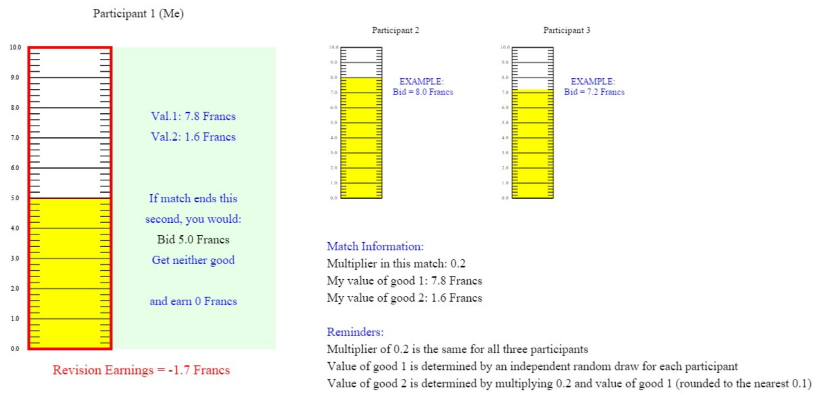
- Remember, duration of each match is RANDOM. Specifically, each match will last at least 20 seconds, but after the first 20 seconds, each additional second, there will be a 1% chance that the match will end and 99% chance that the match will continue. Therefore, the expected length of each match is 20+100=120 seconds or 2 minutes. However, some matches will be shorter and some matches will be longer due to chance.

Task 4 Revise your bid to $4.0.

- The actual decision screen will include decision boxes for the participants with whom you are matched. If you change your bid or one of the participants that you are matched with changes his/her bid, your earnings for the match may change. Thus, even if you don't change your bid, revisions by other participants may result in different earnings. Note that presented outcome will be for the case of the match ending that second.

Task 5 Revise your bid to $5.0.

Examples



Example Explanation (Change your bid to see how explanation changes).

- Your value of good 1 was randomly drawn to be 7.8 Francs
- Your value of good 2 was obtained by multiplying 0.2 and 7.8
- Your current bid is 5.0 Francs
- Your current bid is the third highest among the three. Therefore, you get neither good 1 nor good 2.
- So if the match were to end this second, you would earn 0 Francs minus revision earnings.

Notes:

1. In the actual experiment, you will not see bids by the participants that you are matched with.
2. Everyone will be able to revise their bids at any moment in time.
3. You will see your earnings for the case if the match were to end this second.
4. Your earnings may be positive, negative, or zero depending on action by you and the participants that you are matched with.

[Click Here for Another Example]

A.4 Additional Figures and Tables

Table A.5.: Match Duration (Seconds).

Match:	1	2	3	4	5	6	7	8	9	10
Number of Seconds:	37	166	172	108	176	181	25	145	146	57

Table A.6.: Subject Bid-to-Value Ratios in Sessions 1-4

	(a) Highest-valued			(b) Medium-valued			(c) Lowest-valued		
	$C = 0.0$		$C = 0.1$	$C = 0.0$		$C = 0.1$	$C = 0.0$		$C = 0.1$
$\alpha = 0.2$	0.964 (0.04)	$\overset{0.302}{\sim}$	0.912 (0.027)	0.955 (0.05)	$\overset{0.602}{\sim}$	0.916 (0.051)	2.359 (0.331)	$\overset{0.303}{\sim}$	1.887 (0.311)
	$\gg^{0.022}$		$\gg^{0.048}$	$\sim^{0.346}$		$\sim^{0.213}$	$\sim^{0.591}$		$\sim^{0.546}$
$\alpha = 0.5$	0.83 (0.039)	$\overset{0.577}{\sim}$	0.794 (0.05)	0.876 (0.063)	$\overset{0.591}{\sim}$	0.838 (0.033)	2.606 (0.298)	$\overset{0.019}{\gg}$	1.642 (0.247)
	$\sim^{0.433}$		$\sim^{0.605}$	$\sim^{0.667}$		$\sim^{0.963}$	$\sim^{0.163}$		$\sim^{0.444}$
$\alpha = 0.8$	0.765 (0.076)	$\overset{0.933}{\sim}$	0.757 (0.047)	0.835 (0.065)	$\overset{0.946}{\sim}$	0.841 (0.055)	1.991 (0.289)	$\overset{0.113}{\sim}$	1.363 (0.232)
	$\ll^{0.019}$		$\lll^{0.006}$	$\sim^{0.15}$		$\sim^{0.337}$	$\sim^{0.431}$		$\sim^{0.217}$
$\alpha = 0.2$	0.964 (0.04)		0.912 (0.027)	0.955 (0.05)		0.916 (0.051)	2.359 (0.328)		1.887 (0.307)
Average:	0.861 (0.031)	$\overset{0.397}{\sim}$	0.827 (0.026)	0.893 (0.035)	$\overset{0.562}{\sim}$	0.867 (0.027)	2.348 (0.181)	$\overset{0.006}{\ggg}$	1.655 (0.161)

Notes: **Panel (a)** presents average bid to value ratio per match across subjects with the highest private value in each group. **Panel (b)** presents average bid to value ratio per match across subjects with the second highest private value in each group. **Panel (c)** presents average bid to value ratio per match across subjects with the lowest private value in each group. Bootstrapped standard errors are in parentheses. $>$, $\gg$, and $\ggg$ denote significance at 0.10, 0.05, and 0.01 levels, respectively. P-values are determined using two-tailed permutation tests.

Table A.7.: Subject Bid-to-Value Ratios in Sessions 5-8

	(a) Highest-valued			(b) Medium-valued			(c) Lowest-valued		
	$C = 0.0$		$C = 0.1$	$C = 0.0$		$C = 0.1$	$C = 0.0$		$C = 0.1$
$\alpha = 0.2$	0.94 (0.05)	$\sim^{0.44}$	0.889 (0.04)	0.946 (0.055)	$\sim^{0.608}$	0.91 (0.035)	3.294 (0.65)	$\ggg^{0.002}$	1.45 (0.209)
	$\sim^{0.223}$		$\sim^{0.107}$	$\sim^{0.842}$		$\sim^{0.756}$	$\sim^{0.416}$		$\sim^{0.149}$
$\alpha = 0.5$	0.848 (0.052)	$\sim^{0.418}$	0.793 (0.039)	0.963 (0.062)	$\sim^{0.403}$	0.888 (0.059)	5.023 (1.736)	$\ggg^{0.0}$	1.041 (0.173)
	$\gg^{0.049}$		$\sim^{0.252}$	$\ggg^{0.001}$		$\sim^{0.129}$	$\sim^{0.361}$		$\sim^{0.524}$
$\alpha = 0.8$	0.695 (0.052)	$\sim^{0.864}$	0.709 (0.058)	0.659 (0.057)	$\sim^{0.298}$	0.751 (0.065)	3.138 (1.04)	$\gg^{0.031}$	1.224 (0.208)
	$\lll^{0.002}$		$\ll^{0.02}$	$\lll^{0.0}$		$\ll^{0.038}$	$\sim^{0.906}$		$\sim^{0.474}$
$\alpha = 0.2$	0.94 (0.049)		0.889 (0.041)	0.946 (0.055)		0.91 (0.035)	3.294 (0.647)		1.45 (0.208)
Average:	0.828 (0.032)	$\sim^{0.483}$	0.797 (0.029)	0.856 (0.038)	$\sim^{0.901}$	0.85 (0.032)	3.818 (0.713)	$\ggg^{0.0}$	1.239 (0.114)

Notes: **Panel (a)** presents average bid to value ratio per match across subjects with the highest private value in each group. **Panel (b)** presents average bid to value ratio per match across subjects with the second highest private value in each group. **Panel (c)** presents average bid to value ratio per match across subjects with the lowest private value in each group.

Table A.8.: GSP Efficiency

Sessions 1–4

	$C = 0.0$		$C = 0.1$
$\alpha = 0.2$	0.936 (0.029)	$\sim^{0.567}$	0.958 (0.028)
	$\sim^{0.939}$		$\sim^{0.52}$
$\alpha = 0.5$	0.932 (0.031)	$\sim^{0.15}$	0.984 (0.009)
	$\sim^{0.327}$		$\sim^{0.259}$
$\alpha = 0.8$	0.972 (0.016)	$<^{0.07}$	0.997 (0.002)
	$\sim^{0.379}$		$\sim^{0.204}$
$\alpha = 0.2$	0.936 (0.028)		0.958 (0.027)
Average:	0.944 (0.016)	$<^{0.083}$	0.978 (0.011)

Sessions 5–8

	$C = 0.0$		$C = 0.1$
$\alpha = 0.2$	0.916 (0.031)	$<^{0.064}$	0.976 (0.009)
	$\sim^{0.78}$		$\sim^{0.188}$
$\alpha = 0.5$	0.927 (0.033)	$\ll^{0.025}$	0.99 (0.004)
	$\sim^{0.43}$		$\sim^{0.803}$
$\alpha = 0.8$	0.963 (0.022)	$\sim^{0.447}$	0.981 (0.013)
	$\sim^{0.239}$		$\sim^{0.779}$
$\alpha = 0.2$	0.916 (0.03)		0.976 (0.01)
Average:	0.935 (0.017)	$\lll^{0.007}$	0.982 (0.005)

Notes: Unit of observation is a matched group of subjects. Bootstrapped standard errors are in parentheses. $>$, $\gg$, and $\ggg$ denote significance at 0.10, 0.05, and 0.01 levels, respectively. P-values are determined using two-tailed permutation tests.

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EDUCATION

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RESEARCH INTERESTS

Interests: Economics and Policy Implications of Emerging Technologies, Augmented and Virtual Reality Applications, Applied Machine Learning and Statistics.

Methodologies: Econometrics, Experiments, Machine Learning & Data Mining of Unstructured Data, Deep Learning, Bayesian Inference, and Computational Modeling

WORKING PAPERS

"Using Machine Learning for Modeling Human Behavior and Analyzing Friction in Generalized Second Price Auctions" *with Yaroslav Rosokha and Karthik Kannan*
(Under 3rd round review at Information Systems Research)

"The Impact of an Augmented-Reality Game on Local Businesses: A Study of Pokémon Go on Restaurants" *with Warut Khern-am-nuai and Karthik Kannan*
(Invited for 3rd round review at Information Systems Research)

- Media mentions: *Growth Business UK, QSR Media, University Chronicle, Eatout Magazine, Les Affaires*

"Status Downgrade: The Impact of Losing Status on User Generated Content Platform" *with Wreeto Kar and Warut Khern-am-nuai (In progress)*

CONFERENCE PRESENTATIONS

- Pamuru, V., Kannan, K., and Rosokha, Y. "Using Machine Learning for Modeling Human Behavior and Analyzing Friction in Generalized Second Price Auctions," Workshop on Information Technology Systems (WITS), Munich 2019 *(Best Paper Runner-up)*

- Pamuru, V., Kar, W., and Khern-am-nuai, W. "Status Downgrade: The Impact of Losing Status on User Generated Content Platform," Workshop on Information Systems and Economics (WISE), Munich 2019
- Pamuru, V., Khern-am-nuai, W., and Kannan, K. "The Impact on Augmented Reality Games on Real World Businesses," Conference on Digital Experimentation (CODE) @ MIT, Boston 2019
- Pamuru, V., Kannan, K., and Rosokha, Y. "Using Machine Learning for Modeling Human Behavior and Analyzing Friction in Generalized Second Price Auctions," INFORMS Conference, Seattle 2019
- Pamuru, V., Khern-am-nuai, W., and Kannan, K. "The Impact on Augmented Reality Games on Real World Businesses," INFORMS Conference, Seattle 2019
- Pamuru, V., Khern-am-nuai, W., and Kannan, K. "The Impact of an Augmented-Reality Game on Local Businesses: A Study of Pokémon Go on Restaurants," Statistical Challenges in Electronic Commerce Research (SCECR), Hong Kong 2019
- Pamuru, V., Khern-am-nuai, W., and Kannan, K. "The Impact of an Augmented-Reality Game on Local Businesses: A Study of Pokémon Go on Restaurants," Workshop on Information Systems and Economics (WISE), San Francisco 2018
- Pamuru, V., Kannan, K., and Rosokha, Y. "Generalized Second Price Auction with Frictions: A Study of Efficiency and Bidding Behavior," Conference on Information Systems and Technology (CIST), Phoenix 2018
- Pamuru, V., Kannan, K., and Rosokha, Y. "Generalized Second Price Auction with Frictions: A Study of Efficiency and Bidding Behavior," Statistical Challenges in Electronic Commerce Research (SCECR), Rotterdam 2018
- Pamuru, V., Kannan, K., and Rosokha, Y. "Generalized Second Price Auction with Frictions: A Study of Efficiency and Bidding Behavior," Workshop on Experimental And Behavioral Economics In Information Systems (WEBEIS), Arlington 2018
- Pamuru, V., Kannan, K., and Rosokha, Y. "Using Machine Learning to model Human Behavior: Studying Frictions in GSP Auctions," Production and Operation Management (POMS) Conference, Houston 2018
- Pamuru, V., Khern-am-nuai, W., and Kannan, K. "When Virtual Meets Real: The Effect of Pokémon Go on Local Restaurants," International Conference on Information systems (ICIS), Seoul 2017
- Pamuru, V., Khern-am-nuai, W., and Kannan, K. "When Virtual Meets Real: The Effect of Pokémon Go on Local Restaurants," Conference on Information Systems and Technology (CIST), Houston 2017
- Pamuru, V., Khern-am-nuai, W., and Kannan, K. "The Impact on Augmented Reality Games on Real World Businesses," Production and Operation Management (POMS) Conference, Seattle 2017

WORKSHOPS & SYMPOSIUMS

- *Presenter and Discussant (with Travel grant),* Wharton Innovation Doctoral Symposium (WINDS), Philadelphia 2019

- *Fellow* – POMS Doctoral Consortium, 2019
- *Participant*, Summer Workshop on Machine Learning, Carnegie Mellon University, Pittsburgh 2019
- *Participant*, Structural Modeling and Machine Learning Applications for Research on Technology (SMART) Workshop, University of Washington, Seattle 2017
- *Participant*, Quantitative Marketing and Structural Econometrics (QMSE) Workshop, Washington University, St Louis 2017

HONORS & AWARDS

- *Best Paper Runner-up Award* – Workshop on Information Technology Systems (WITS), 2019
- *Research Grant* – Google Cloud, 2019
- *First place* – Summer ML Workshop's Competition, Carnegie Mellon University, 2019
- *Purdue Research Foundation (PRF) Fellowship*, Purdue University, 2018
- *MIS area award* – Krannert School of Management, Purdue University, 2018
- *Community Service Award* – SSSP Inc, Perth, 2018
- *Best Presentation* – Krannert Research Symposium, Purdue University, 2017 & 2018
- *Dean's Award* – Krannert School of Management, Purdue University, 2017
- *Purdue Graduate Student Travel Grant* – Purdue University, 2017 & 2018
- *Academic Associate of the Year* – Indian School of Business (ISB), 2015

SERVICE & AFFLIATIONS

- *Ad hoc Reviewer* – ICIS 2017, ICIS 2018, ICIS 2019, CIST 2019, CIST 2018
- *President* – Krannert Doctoral Student Association, 2017
- *Senator* – Purdue Graduate Student Government, 2016
- *President* – Toastmasters Club, 2013

TEACHING EXPERIENCE

Purdue University - Instructor

- MGMT 382, Management Information Systems
  - Summer 2019 – *Online course*

Purdue University – Teaching Assistant [2015 – present]

- MGMT 582, Management of Organizational Data
  Prabuddha De - Spring 2016, Fall 2018, Fall 2019
- MGMT 683, Management Information Systems,
  Karthik Kannan - Spring 2016, Spring 2017, Fall 2016, Fall 2017
- MGMT 488, Electronic Commerce and Information Strategies
  Mohammad Rahman - Spring 2016
- MGMT 687, Designing for Human Instincts
  Karthik Kannan - Fall 2015, Fall 2016
- MGMT 382, Management Information Systems
  Zaiyan Wei - Spring 2017

Indian School of Business, Hyderabad - Academic Associate [2014 –2015]

- Leveraging Web – Social Media, Online Advertising and Web Analytics
  Anindya Ghose & Amit Mehra - 2014
- Technology Strategy and Consulting
  Rajiv Banker & Nishtha Langer - 2014
- Forecasting Analytics
  Galit Shumeli - 2015
- Business Analytics using Data Mining
  Anitesh Barua & Shwandra Hill - 2015
- Statistical Methods for Managerial Decisions
  Sarang Deo - 2015
- Strategies for Digital Economies
  Deepa Mani & Anitesh Barua - 2015

PROGRAMMING SKILLS

- Programming: Python, R, Shell, Javascript, HTML
- Machine Learning: Tensorflow, Scikit-learn, NLTK, Pytorch
- Database: SQL, MySQL, MS Access, PostgresSQL, NoSQL, MongoDB
- Visualization: Tableau, PowerBI, pyplot, ggplot2
- Statistics: STATA, Matlab, R

CERTIFICATIONS

- Project Management Professional (PMP), 2013
- Competent Communicator (CC) - Toastmasters Club, 2012
- Certified on Training Needs Analysis, Design of Training & Direct Training Skills by Department of Personnel and Training, Government of India, 2013

PROFESSIONAL EXPERIENCE

Indian School of Business (ISB), Hyderabad [Jul 2014 – Jun 2015]
- Academic Associate

Screenroot Technologies Pvt Ltd [Feb 2011 - Nov 2012]
- Project Manager – Web & Mobile Application Design

Swiftant IT Solutions Pvt Ltd [Sep 2009 – Jan 2011]
- Programmer Analyst – Web Application Development

MEDIA COVERAGE

Krannert Magazine: "The Pokémon Paradox. Krannert researchers examine the costs and benefits of popular game." Spring 2018.(https://krannert.purdue.edu/konline/2018s/features/pokemon1.php)

Eat Out Magazine: "Augmented Reality Apps Increase the Profits of Restaurants." October 3, 2017. (http://eatoutmagazine.co.uk/augmented-reality-apps-increase-profits-restaurants)

QSR Media UK: "Augmented reality apps increase restaurants' profits in gaming hot spots." October 3, 2017. (http://qsrmedia.co.uk/technology/news/augmented-reality-apps-increaserestaurants-profits-in-gaming-hot-spots)

University Chronicle: "Augmented reality apps cause restaurant profits to rocket" (https://www.ssuchronicle.com/2017/10/03/augmented-reality-apps-cause-restaurant-profits-to-rocket/)

Growth Business UK: "How restaurants can use augmented reality to cash in." October 3, 2017. (http://www.growthbusiness.co.uk/how-augmented-reality-helps-restaurants-cash-in2552454/)

Les Affaires: "Pokémon Go est-il bon pour le commerce?" May 17, 2017. (http://www.lesaffaires.com/blogues/l-economie-en-version-corsee/pokemon-go-est-il-bonpour-le-commerce/595004)