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Essays on Online Platforms: Policy and Monetization Strategies

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Abstract

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This dissertation analyzes the digital platform from two aspects, the platform policy, and the monetization strategies. Based on three different settings, the sharing economy, the user-generated content platform, and the digital game platform, I study how the development of online platforms reshape the consumer decision and the supplier's choice, and how the online platforms would accommodate for the change. In the first essay, I investigate how the platform-side picture disclosure would influence the consumers' decision. I find that consumers can better identify the heterogeneous quality when pictures are disclosed as quality signals. However, the efficiency is affected when consumers misinterpret the supplier's quality from the image. In the second essay, I examine how the peer-based monetary incentive would influence the content generator's participation. I find that the peer-based monetary incentive increases the content

contribution but may have a temporary negative impact as content generators tend to overestimate their ability to monetize the content. The heterogeneous effect on content generators' intrinsic motivation is also discussed. In the third essay, I study the optimal pricing of the virtual selling strategy, where the premium module can be obtained not only through direct purchase but also through virtual currency earned during excessive gameplay. I build an analytical model to describe the player's tradeoff of money and time and find a reverse-discrimination effect and a complementary effect, which enable the game provider to provide time discounts to the players, but in the meantime, make more profit. The business implications and theoretical contributions are discussed in each essay.

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Chapter 1. INTRODUCTION

The past years have witnessed a tremendous growth in the digital economy. An increasing number of industries have started to adopt online platforms to facilitate transactions, deliver information, and promote consumer engagement. The implementations of online platforms have expanded from the retail industry to other industries, such as social media, transportation, gaming industry. My studies are based on three different areas in the online platform—namely, the sharing economy, user-generated content platforms, and digital gaming platforms.

The unique characteristics of online platforms have reshaped the consumers' behavior, influenced the supplier's strategies, and fostered the novel profit models of the platforms. Distinct from the traditional industry, many online platforms rely on the effort of the "peers" to promote transactions and to provide service. On these platforms, users can be both a service supplier and a consumer. Examples include the sharing economy such as Uber and Lyft (where riders can also provide the driving service as a driver) and the user-generated content (UGC) platforms such as Youtube and Reddit (where content consumers can also post videos and articles as content generators).

The reliance on the effort of peers, although facilitating the growth of the online platforms, leads to two major challenges. The first challenge is the service quality. When the suppliers are no longer professionals, consumers face a higher risk when consuming products or content. A relevant issue is information asymmetry, where consumers have limited information about the product before purchase. The change in the significance of product information could influence the consumers' information-seeking and purchase behavior. The second challenge is the motivation of suppliers. For instance, the UGC platform depends heavily on the involvement of content

generators, who need to invest significant effort in producing the high-quality content. However, although all users can be content generators on these platforms, only a small portion involves in the content production process.

The platforms have implemented various policies and launched different features to address the concerns of the uncertainty in product quality and a lack of incentive for suppliers. Motivated by the challenges that the online platform encounter (due to the behavior change of the suppliers and consumers) and the innovative business practice that the platform has come up with, I start by investigating two specific topics. First, how information disclosure, a method to reduce the consumers' uncertainty of a product quality, would influence the consumers' behavior. Second, how monetary incentives would influence the service provider's contribution in the online platform.

In Chapter 3, I study how disclosing picture information as a quality signal would reshape the consumer behavior in the sharing economy. The sharing economy has experienced rapid growth in recent years. Despite the social and economic impact, the sharing economy platform suffers from information asymmetry and a lack of government enforcement. Apart from customer reviews, platform disclosure is also a valuable source to provide quality signals. While most platforms use badges to help with consumer decisions, more platforms have started disclosing picture information. I investigate the impact of picture disclosure on consumer's purchase behavior and the role of platform disclosure among other quality-enhancing mechanisms, such as reputation and market competition. The analysis is based on the data from a large peer-to-peer meal-sharing platform in China. The platform conducts onsite hygiene inspection to evaluate the suppliers' hygiene quality and discloses kitchen pictures as the hygiene quality signal. I integrate an econometric analysis method with deep-learning and computer-vision techniques and find that,

although the disclosure leads to an overall sales increase, suppliers with a passing but relatively low hygiene quality suffers from a sales decrease. Besides, disclosing images can create misinterpretation due to the noise in the quality signal, resulting in a non-monotonic impact on sales as related to the platform evaluated hygiene quality. I also find that the effect is attenuated when market competition is intense or when the supplier's reputation on hygiene quality is high. This work extends the previous studies, which focus on the positive role of platform disclosure by highlighting that the informative effect of disclosing pictures overweighs the qualification effect and that the noise in pictures can still lead to suboptimal outcomes. It also integrates the enforcement method from the three main parts of the sharing economy ecosystem – suppliers in terms of market competition, consumers in terms of online review, and the platform in terms of picture disclosure.

In Chapter 4, I study the impact of a novel monetary incentive, peer-based monetary incentive, on the content generators' behavior in a user-generated content platform. The value of user-generated content (UGC) has been widely studied in the past years. Recently, practitioners involve monetary incentive to motivate the content generation process. Several platforms apply a peer-based monetary incentive, where the incentive comes from the content consumers' voluntary support, which works similar to "tips" in a restaurant. Using data from a Chinese UGC social platform that implements the "tipping" policy, I investigate how the peer-based monetary incentive would influence the content generation behavior. I first construct a panel analysis and find that the writers' participation increases when the policy is launched but no money has been collected by the writer. When the writer receives her first tip, however, her participation decreases. I construct a structural model that accommodates for the writer's learning behavior of her monetary and social value. The result shows that monetary value posits a positive and concave impact on content

generation, indicating that the tipping policy is an effective tool to motivate the content generators. Writers, on the other hand, tend to overestimate their ability to monetize their content when the policy is first implemented, leading to a negative adjustment of the participation behavior when she receives more signals of her monetization ability. This work shows that although monetary incentive often hurts prosocial behavior due to the deterioration of the individual's altruism image, a proper design combining user appreciation and monetary incentive can work effectively. A further analysis identifies three latent groups of writers, each of which reacts differently to the social and the monetary incentive.

The unique characteristics of online platforms influences not only the behavior of service suppliers and consumers but also the profit model of the online platforms. One may find that many products and services that used to be charged can now be obtained for free. For instance, consumers can get access to news articles in the websites without purchasing a newspaper. Similarly, an increasing number of digital game companies have started launching the free-to-play games, where players can download and play the game for free. These firms can gain profit through other channels, such as platform traffic or the game playtime, without directly charging the consumers. The novel business model encouraged me to investigate how this monetizing strategy would influence the platform's selling strategy as well as the consumer's welfare.

In Chapter 5, I study the impact and value of the freemium pricing strategy in the free-to-play digital games. Providers of free-to-play games often gain revenue by monetizing players' playtime, e.g., through in-game advertising, and by selling premium module of the game. One emerging strategy to sell the premium module, known as the virtual selling strategy, is to set the module price based on an amount of virtual currency which players can either spend playtime to earn or use real currency to buy. I examine how the virtual selling strategy leads to different market

outcomes than the traditional real selling strategy where players can purchase the premium module using real currency directly only. I focus on the differences caused by one specific feature – players can pay for the module indirectly using their playtime in the virtual selling strategy. I show that when the provider's efficiency of monetizing players' playtime, i.e., the time revenue rate, is above a threshold, the virtual selling strategy will benefit the provider and hurt the overall consumer surplus compared to the real selling strategy even though (i) the virtual selling strategy results in reverse price discrimination in the market equilibrium and (ii) players in the virtual selling strategy have one additional way, i.e., using their playtime, to pay for the module. I identify an undocumented complementary effect which causes the profit augmentation under reverse discrimination and the surplus reduction. The complementary effect also results in a U-shaped relationship between the equilibrium module price and the time revenue rate in the virtual selling strategy when the module only provides a small number of new gaming stages. It contradicts the traditional result from the real selling strategy that the provider shall reduce the module price when she becomes more efficient in monetizing players' playtime.

Chapter 2. RELATED LITERATURE

I study the policies and the monetization strategies in the digital platform based on three different contexts. In this section, I review the literature in relevant fields and illustrate how my work extends the understanding of the previous studies. Section 2.1 shows the related literature in the sharing economy, information asymmetry, and information disclosure strategies. Section 2.2 reviews the studies on monetary incentive and user-generated content. Section 2.3 presents the literature in digital games, freemium modeling, and the ad-sponsored model.

2.1 SHARING ECONOMY AND INFORMATION DISCLOSURE

My first work relates to the broad stream of literature on sharing economy, information asymmetry, and information disclosure.

The sharing economy has a significant impact on the traditional industry and society. Zervas et al. (2017) show that Airbnb entry has a causal effect of 8% - 10% on the hotel revenue, and Li and Srinivasan (2019) further show that Airbnb can compromise the demand fluctuation in the hotel industry. The sharing economy can benefit users by reducing consumers' costs (Santi et al. 2014) and alleviating the risk of potential unemployment (Huang et al. 2019). It can also benefit the social welfare. Ride-sharing platforms, for instance, can help to reduce the mobile fatalities (Greenwood and Wattal 2017), and to reduce the emission from vehicles (Santi et al. 2014).

Despite the benefits, the sharing economy suffers from the uncertainty of product and service quality. The concern originates from the standard information asymmetry problem (Akerlof 1970), where suppliers have more information about the product or service quality than do consumers (Healy and Palepu 2001). In the sharing economy, information asymmetry has been the main issue as consumers have limited offline information before purchase (Cohen and Sundararajan 2015).

Using analytical models, Rochet and Tirole (2006) show that in a two-sided market like the sharing economy, information asymmetry will lead to a subsidization of platform transactions. Weber (2014) shows that sharing economy can suffer from the moral hazard problem. Other literature further points out that sharing economy is considered a legal gray area, adding challenges to disclosure from government enforcement. Katz (2015) shows that when suppliers use their underutilized personal assets for commercial purposes, the distinction between “commercial” and “personal” becomes unclear. Therefore, government disclosure, the standard method to prevent information asymmetry, is not directly available to the sharing economy (Rauch and Schleicher 2015).

To address the concern of information asymmetry, consumers should get access to quality signals. I consider the quality signal from two general perspectives: the quality signal in the traditional food industry and the quality signal in online platforms.

I further categorize the quality signal in the traditional food industry into two types: product health information disclosure and restaurant inspection disclosure. As for food information disclosure, Cawley et al. (2018) find that disclosing calorie information negatively influences the total calorie of foods ordered in a restaurant. A similar topic has been investigated in fast-food restaurants with mixed findings (Bollinger et al. 2011, Elbel et al. 2009). Restaurant inspection disclosure relates more to our work. Bederson et al. (2018) analyze the voluntary disclosure of hygiene inspection results and find that suppliers with Grade A- are most likely to disclose. Jin and Leslie (2003) find that revealing a higher hygiene grade leads to a greater increase in the supplier’s sales performance. Jin and Leslie (2009) find that both the reputation incentive and posting a grade card bring improvements in restaurant hygiene.

Online platforms often use customer reviews and platform disclosed information as the quality signals. The customer review is broadly applied to provide quality signals in the online platforms. Previous studies have shown the significant impact of reviews on customer behavior (Chevalier and Mayzlin 2006, Wu et al. 2015). Despite its effectiveness, the rating can be influenced by multiple factors, such as the platform's rating environment (Moe and Schweidel 2012, Ho et al. 2017) and the ratings by previous consumers (Lee et al. 2015). Besides, studies also find that reviews can be contaminated by spam users (Jindal and Liu 2008). These studies indicate that consumer review is not objective in describing the product quality of a supplier, hurting its credibility.

Another source of the quality signal is platform disclosure. Prior research shows that displaying a badge of a supplier that indicates competence or charity collaboration can lead to a significant increase in demand (Elfenbein et al. 2015, 2012). Although a badge can help with consumer decisions, it only provides a binary signal of a supplier's qualification. Some platforms have started using platform-offered pictures as quality signals. Zhang et al. (2017) find that pictures taken by platform professionals differ from the supplier's own taken pictures in several image characteristics and that the former can attract higher demand.

When considering consumers' purchasing behavior, this work also relates to the consumers' perceived value. When making purchase decisions, consumers rely on the perceived value (e.g., perceived quality) of a product, which depends on their subjective evaluations rather than the supplier's assessment (Wu et al. 2014, Woodruff 1997). In our case, for instance, consumers are more likely to make purchase decisions based on the perceived hygiene quality instead of the platform evaluated hygiene quality.

The quality signal of a product can influence the consumer's perceived value (Kirmani and Rao 2000). When the signal is delivered through unstructured data such as pictures and texts, consumers need to invest extra effort to extract and comprehend the information (Engelberg 2008). For instance, longer articles take greater cognition resources to comprehend (Pan and Zhang 2011). Given the limited cognition resources, reports that are less readable can lead to biased individual perceptions, which influences the market efficiency (Bloomfield 2002, Lehavy et al. 2011).

Our work extends the understanding of quality signals revealed through pictures. Previous studies demonstrate the significance of information disclosure. However, they often examine the value of either a binary platform-offered certification or structured information such as review ratings. Studies that explore the value of unstructured information usually focus on text information and the impact of platform-disclosed pictures is rarely investigated. Prior work that analyzes the value of pictures focus on the positive role of fabricated or professionally taken pictures. I focus on the heterogeneous impact of pictures by combining both the positive role (i.e., qualification effect) and the role to deliver more comprehensive information (i.e., informative role). I also investigate the potential market inefficiencies due to the interpretation of picture information.

2.2 MONETARY INCENTIVE AND UGC PRODUCTION

My second essay studies how the peer-based monetary incentive would influence the UGC content generation. It relates to two the literature in monetary incentive and user-generated content.

Monetary incentive has been broadly applied to motivate individuals' engagement, effort, and performance. Standard economic reasoning suggests that monetary incentive has a positive effect on individuals' preferred behavior, assuming that individuals are rational. The monetary incentive has been found effective in multiple settings, such as encouraging school attendance to students

(Fryer 2011) and engaging in healthy activities (Volpp et al. 2009). It is also applied in various fields of business applications from motivating the performance of CEO (Baker et al. 1998) to encouraging survey feedback after purchase (James and Bolstein 1992).

However, the monetary incentive is not always effective in motivating the favorable behavior. Studies have shown that for prosocial behavior where individuals contribute due to their altruism and interest, the monetary incentive can fail, which is often referred to as the crowd out effect (Frey and Jegen 2001). Richard Titmuss (1970) argued that providing monetary incentives can lead to a decrease in high-quality blood donors. Ariely et al. (2009) found that the monetary incentive would dilute the signal of prosocial acts and decrease the contributor's image value. As a side effect, a small amount of monetary incentive or monetary penalty is found to backfire – the preferable behavior reduces, and the non-preferable behavior increases, which is also known as the W effect (Gneezy et al. 2000, Gneezy and Rustichini 2000). Bénabou and Tirole (2006) argued that this is because monetary incentive can be interpreted as a profit-seeking behavior, hurting the image of the contributors, which consequently hurts the participation.

Researchers have spent significant effort exploiting the methods to promote UGC production, a type of prosocial behavior. An abundance of research has investigated the influence of non-monetary factors, such as social capital gain and the network effect, on the content generation behavior (Hennig-Thurau, 2004; Shen et al. 2015; Lerner and Tirole 2002; Daugherty et al. 2008). For instance, Zhang and Zhu (2011) show that a reduction in audience size leads to a decrease in UGC production. Similarly, Zhang and Wang (2012) show that the network structure can effectively influence the production of UGC contents. The social capital gain is also shown to be effective in promoting the content generation and knowledge sharing behavior (Ma and Agarwal 2007, Toubie and Stephen 2013). The influence of peers is also investigated. For instance, Burtch

et al. (2019) have found that the peer-initiated non-monetary incentive through badges can increase content generation.

Studies that analyze the impact of monetary incentives on the UGC production usually focus on the subarea where contents are product reviews. Moreover, the monetary incentive is often provided by either the seller or the platform owner. Avery et al. (1999) consider the product review as a public good and applies an analytical model to show that monetary incentive can address the concern of under-provision of review comments and motivate content production. Following a similar idea, Golle et al. (2011) design several methods to promote content sharing in a peer-to-peer network network. Despite the effectiveness to increase review production, abundant research found that monetary incentive posits a negative impact of the content quality. For instance, Burtch et al. (2017) show that monetary incentive, by itself, increases the number of review but decreases the length of each review.

The focus on the online e-commerce setting restrains the provider of the monetary incentive to either the platform or the product supplier, which further emphasizes the “extrinsic” role of the monetary incentive, leading to a profit-seeking behavior – consumers who write the review often sacrifice the quality for quantity. The setting of my work, however, differs from those of the prior works’ by having “peers” as the provider of the monetary incentive, which combines the extrinsic role (i.e., profit-making) and the intrinsic role (i.e., obtaining the appreciation from the peers). Moreover, the peer-based monetary incentive also obtains the “quality-contingent” feature by making the monetary incentive “voluntary” in the form of tips.

2.3 DIGITAL GAMES, FREEMIUM MODEL, AND AD-SPONSORED MODEL

My third essay relates to three streams of literature: digital games, the freemium business model, and ad-sponsored model.

Extant literature of digital games focused on players' motivation to gameplay. They showed that factors such as gaming pleasure, challenges, reputation, and interaction with other players are positively correlated with a player's gaming intention, engagement, and royalty (Hsiao 2007; Yee 2006; Zhang et al. 2015). Longer playtime indicates a higher level of engagement (Liu et al. 2013). In most games, players can purchase gaming content to boost their gameplay experience (Soroush et al. 2014; Guo and Barnes 2011). Researchers have found that player's purchase decision is associated with content attributes, game environment, context change, as well as players' own preference (Chung 2005; Lehdonvirta 2009). To stimulate purchase and increase gameplay, providers have started to offer free-to-play games. These games consist of free content that is available to all players, and premium content that is available only after purchase. While some players are unwilling to spend extra time on the game, others would like to contribute more time and obtain premium content without direct purchase (Evans 2016; Lee and Lin 2011; Castronova 2006). Guo et al. (2018) analytically studied the situation where premium content is priced based on virtual currency and players can buy virtual currency using real currency. The paper focused on investigating the optimal exchange rate between the real currency and the virtual currency.

Purchasing premium content in a free-to-play game fits the scenario of freemium business models. Niculescu and Wu (2014) compared the feature-limited freemium model with uniform seeding – a business model that is popular in software selling – and benchmarked both models against the conventional model “charging for everything”. They found that feature-limited model could be a firm's optimal choice when consumers' prior valuations on premium content are either

relatively low or high. Lee and Tan (2013) empirically identified the factors that lead to the adoption of both feature-limited and time-limited freemium software. They showed that there does not exist discernible differences between two types of freemium regarding their impact on sampling performance. Liu et al. (2014) utilized a large panel data set to show that adopting the freemium strategy will lead to increased sales of the paid mobile apps. They also showed that the quality of the free app is one of the key factors in boosting the sales. Ray et al. (2016) proposed an objective approach that helps a vendor to decide which features to include in his free demonstration. Our study adopts the freemium framework to capture the nature of free-to-play games. I intend to analyze characteristics of the virtual selling strategy and provide pricing suggestions to game providers. Therefore, instead of comparing freemium models with other business models, I focus on one specific type of freemium model to better emphasize agents' reaction towards the virtual selling strategy under freemium setting. Zhang et al. (2016) set up a game theoretical model to study the impact of free offering on a duopoly competition in the presence of network effects. Either of two firms chooses between offering a core product along with a paid service and offering them as a bundle. They found that when the qualities of the core product were sufficiently differentiated across two firms, the firm with the superior product quality would opt in the bundling strategy while the other firm with the inferior product quality would choose to offer them separately. When the qualities are similar, two firms will choose the same strategy, either bundling or not bundling. Lee et al. (2017) utilized a structural econometric model to investigate the effectiveness of a referral program in freemium selling. They conducted counterfactual analysis which determines the optimal balance of monetization and growth and measured the value of free customers. Mehra and Saha (2017) analytically studied how a software vendor can jointly utilize free trials and public beta when releasing a software application. They

identified the market condition where realizing public beta in addition to free trials is profitable to the vendor.

As I consider a provider's profit from players' playtime, this work also relates to ad-sponsored business model (Prasad et al. 2003; Petiz et al. 2008; Godes et al. 2009). Gabszewicz et al. (2005) investigated the question regarding whether incorporating ads will lead to a lower newspapers' price. They discovered an interesting result that incorporating ads could decrease the newspapers' price even if the majority of the readers are ad lovers. Anderson and Coate (2005) carried out a welfare analysis for the broadcasting industry where television firms offer free programs and receive revenue by incorporating other merchants' ads. They showed that an equilibrium advertising level might be either above or below the corresponding socially optimal level depending on the users' nuisance cost of watching ads. Fan et al. (2007) studied the impact of consumers' online access cost on a firm's choice between profiting from publishing in-content ads and profiting from selling content. They showed that when online access cost is relatively high, the firm should focus on profiting from publishing in-content ads. Kumar and Sethi (2009) utilized the optimal control theory to investigate how to price web content in a dynamic setting when a firm draws revenue from both consumer subscription and ad publishing. Casadesus-Masanell and Zhu (2010) investigated the interaction between ad-sponsored models and other revenue models (e.g., the subscription fee model). They demonstrated how an incumbent can utilize a hybrid of revenue models to deter competition. Sun and Zhu (2013) empirically tested if content providers will tailor their content to attract more traffic to gain ad revenue. They found that once content providers start to gain revenue from the traffic of blogs, they have the incentive to shift the topics of their content as well as improve their content quality. Similarly, an intermediate result in Hao et al. (2017) showed that once a mobile app developer starts to become an in-app ad publisher, she

would reduce her app price to expand the user base. Chen et al. (2016) compared the advertising model with the brokerage model for an online retail platform. One highlight of their findings is that consumers are always better off under the advertising model due to greater sellers' participation. Zhang (2017) provided guidance for a video-hosting platform to choose between the advertising model and the subscription model, both of which generate revenues based on consumers' usage.

This essay contributes to the extant literature in the following way. Most studies regarding digital games focused on one aspect of players' decisions, either playtime or purchase of the premium content. This study accounts for the correlation of the two by modeling players' decisions jointly. I argue that this modeling approach is crucial to understanding players' behavior dynamics and provider's strategies in the virtual selling strategy because players can "trade time for money." In this regard, the paper which is mostly related to our study is Guo et al. (2018). It answered the question whether a provider should allow players to use real currency to buy virtual currency, and if so, what would be the optimal exchange rate between two currencies. Its primary intention is to connect virtual economy with real economy through the classical labor-leisure economic model. This study, instead, assumes that such exchange of the two currencies is allowed in the game. I compare the virtual selling strategy with a different benchmark – the real selling strategy – where players are not allowed to use playtime to purchase the module. To our best knowledge, our paper is the first study that examines how the virtual selling strategy leads to different market outcomes than the real selling strategy due to its permission of using playtime to purchase the module. Meanwhile, I also reveal the answer to a more micro-level question regarding pricing strategies of premium content based on virtual currency, for example, the U-shaped relationship between the module price and the time revenue rate, which contradicts the traditional belief from the real selling

strategy. Finally, our paper is related to the versioning literature (Bhargava and Choudhary 2001, Bhargava and Choudhary 2008, Chellappa and Mehra 2017) since there is price discrimination in our model – players with high time cost (low willingness to pay) will choose to play the free version and only ones with low time cost (high willingness to pay) will consider purchasing the premium module. Note that such price discrimination exists in both the real selling strategy and the virtual selling strategy. Our goal is to reveal the unique properties of the virtual selling strategy that the real selling strategy does not have. In this regard, our paper also differs from the versioning literature as the reason for the virtual selling strategy to improve the provider's profit compared to the real selling strategy is not price discrimination but the complementary effect.

Chapter 3. THE INFLUENCE OF PLATFORM INSPECTION DISCLOSURE ON SHARING ECONOMY: EVIDENCE FROM UNSTRUCTURED DATA

The sharing economy is a peer-to-peer business whereby a digital platform facilitates the transaction between suppliers and consumers (Gansky 2010, Sundararajan 2016). This business practice has recently enjoyed remarkable growth and attracted significant attention. Boston Consulting Group showed that by 2016, more than \$23 billion of venture funding has poured to the asset-sharing economy.¹ In 2018, more than 760 million people engaged in the sharing economy in China, with a trading volume of 294.2 billion RMB (around \$42 billion).² Besides, PricewaterhouseCoopers forecasted that the global sharing economy market would increase to about \$335 billion by 2025.³ The first business practices of the sharing economy, such as Uber and Airbnb, provided ride-sharing and room-sharing services, respectively. Similar implications later extended to areas that included food sharing (e.g., EatWith), bike-sharing (e.g., Lime), and niche services, such as pet sitting (e.g., DogVacay).

The peer-to-peer nature of the sharing economy, while facilitating the rapid growth of the industry, raises the concern of the product and service quality (Cohen and Sundararajan 2015). It is not surprising that Airbnb hosts are not professional hoteliers (Li et al. 2015), and most suppliers in a food-sharing platform do not own physical restaurants. When it is the peers, rather than the professional suppliers, who are providing the service, the entry barrier goes down, which increases the uncertainty of the product or service quality and puts the platform at risk from opportunistic

¹ <https://www.bcg.com/en-us/publications/2017/strategy-accelerating-growth-consumer-products-hopping-aboardsharing-economy.aspx>

² Original document: <http://www.sic.gov.cn/archiver/SIC/UpFile/Files/Default/20190301115908284438.pdf>.
News report: <https://apnews.com/1b1e1ee8918091dee2122849905a646d>.

³ <https://deemly.co/blog/sharing-economy-predictions-2017/>

suppliers (Rauch and Schleicher 2015). The media has been criticizing ride-sharing platforms for incidents such as kidnappings, assaults, and deaths,⁴ and room-sharing platforms for racial discrimination (Edelman et al. 2017). Although these concerns do not indicate that the sharing economy performs worse than does the traditional industry, widespread negative reports can cause severe damage to the platform's reputation and jeopardize the development of the sharing economy.

Traditional industries rely on government regulation to guarantee product quality. However, in the sharing economy, government enforcement is often not immediately available due to the peer-to-peer nature. For instance, in a sharing economy, it is unclear whether a product is “personal” or “commercial” (Katz 2015), which, in the traditional industry, are key concepts to determine who are eligible for government enforcement. Therefore, it takes time to design appropriate policies for government enforcement, and the regulation usually lags behind the booming sharing economy.⁵

The increasing concern and a lack of timely government enforcement have called up the attention of both the disclosure of quality information and the implementation of different quality-enhancing methods. In a sharing economy platform, these methods often include market competition, online review, and platform disclosure. Market competition takes advantage of the nature of the online two-sided market that an abundance of suppliers is competing against each other. The pressure that consumers will switch to a competing supplier can motivate suppliers to improve product quality (Gans 2002). Therefore, market competition can be regarded as enforcement from the supplier side, whose effectiveness has been broadly studied (Gaynor 2007, Hart 1983). Meanwhile, online reviews can be considered enforcement from the consumer side - the platforms rely on consumer feedback as the quality signal. This method, also known as the

⁴ <https://money.cnn.com/2018/04/30/technology/uber-driver-sexual-assault/index.html>

⁵ <https://www.abc.net.au/news/2015-08-16/calls-for-regulation-of-home-sharing-economy/6696078>.

reputation mechanism, addresses consumer concerns by reducing information asymmetry (see, for instance, Huete-Alcocer (2017), King et al. (2014), and the literature therein).

The third application to ensure satisfactory performance and provide consumers with quality information is the platform-side quality signals. This approach is also frequently adopted in the sharing economy platforms. For instance, Airbnb shows a “Superhost” badge if a host has consistently provided “extraordinary service”, UberEats provides a “Top Eats” badge for outstanding food suppliers, and DogVacay offers virtual medals for the pet hosts that have passed training courses. Similar practices have been witnessed in other online platforms, such as “Elite” badge for Yelp reviews, and “Trophies” for Reddit posts, etc. Although the method is effective in influencing individuals’ behavior (Elfenbein et al. 2015), showing badges only reveals whether a supplier has met a specific benchmark, and has limited ability to distinguish the suppliers’ heterogeneous quality over a spectrum. Recently, platforms have started to use pictures to signal the suppliers’ quality. For instance, Airbnb began to send professional photographers to take photos of a host’s property and highlight these pictures as “verified.” Some other platforms, such as Uber Eats, also post pictures taken by platform professionals on the supplier’s homepage as a quality signal.

Motivated by the growing implications of using pictures as quality signals, we investigate how consumers react to platform-disclosed images when the supplier’s underlying product or service quality is heterogeneous. The prior study focuses on the positive impact of verified professionally taken photos (Zhang et al. 2017) as these photos have characteristics that are more appealing to consumers. However, pictures may not always be positive signals, especially those that tend to faithfully show the quality of the suppliers. An example is pictures taken during quality inspections. For this type of quality signal, two effects should be considered. On the one hand, the picture

provides a credible signal that a supplier is certified, indicating the supplier's competence. We refer to this positive impact as the qualification effect. On the other hand, pictures through inspections depict the suppliers' condition. Given the heterogeneity in the supplier's product quality, consumers, if putting effort into exploiting the image information, will identify the difference and react differently to the suppliers. We refer to this heterogeneous impact as the informative effect. Notably, the consumer decision depends on the perceived quality, a subjective evaluation using the unstructured picture information. Therefore, the impact of disclosing pictures also depends on the consumer's ability to extract and assess the quality information from pictures.

To investigate the impact of picture disclosure and how the two forces influence consumer decisions, we collect data from a large home-cooked meal-sharing platform in China. The platform investigates the home cook's hygiene quality through onsite inspections, where inspectors evaluate the supplier's hygiene quality based on a rubric and come up with a hygiene grade (hereafter, the "platform evaluated hygiene grade"). The platform will also take pictures during inspection for record. Upon disclosure, the platform shows the home cook's kitchen images, which is usually a frontal view of the kitchen, as the quality signal. We call this an "unstructured disclosure" strategy based on the "unstructured" nature of picture information.

We start the analysis by examining the effectiveness of disclosing pictures and, if effective, the size of the impact. This helps to understand the added value of the platform disclosure strategy. We then examine how the effect differs for variations in the platform evaluated hygiene quality. For instance, will consumers react homogeneously to the hygiene quality signal or heterogeneously? If heterogeneous, will all inspected home cooks benefit from the disclosure strategy, and how will the consumers react given the different hygiene quality? Lastly, as quality-enhancing methods from other players on the platform, such as customer review and market competition, are naturally

embedded in the sharing economy ecosystem, we would like to know how the platform disclosure interacts with these pre-existing methods.

Our method integrates econometric analysis with computer-vision and deep-learning techniques. To accommodate the unstructured disclosure strategy and extract features from pictures, we first apply computer-vision and deep-learning methods to detect the room layout and identify pictures disclosed to consumers. We then use Amazon Mechanical Turk to collect the user's perceived hygiene quality based on the identified images. We also apply the Inception-V4 deep neural network to extract dish image features to cluster dish styles for each home cook, as the cuisine type for a home cook is usually vague. Besides, we distinguish a hygiene-specific reputation from the home cook's general reputation through opinion-mining methods, using the customer's review content.

We apply the difference-in-differences (DiD) method in the panel data analysis. We find that disclosing the inspection results, on average, improves the supplier's sales revenue by 23%. The impact varies for home cooks with different hygiene grades: The ones with a low hygiene grade suffer a sales decrease, and those with a medium hygiene grade enjoy a sales increase. Interestingly, the impact on the sales of suppliers with the highest hygiene grade is statistically insignificant. We also find that, unlike the non-monotonic pattern in the *platform evaluated* hygiene grade, the sales change in consumers' *perceived* hygiene grade follows a monotonic pattern. This result shows that, while consumers react rationally based on their perception of the suppliers' hygiene quality, the inconsistency between the perceived and platform evaluated hygiene grade leads to the non-monotonic impact on the platform evaluated hygiene quality. The difference arises because consumers are unable to specify all details included in the inspection procedure from the disclosed pictures. Further, we investigate how the enforcement from the platform (i.e., platform disclosure)

interacts with the enforcement from other players of the sharing economy ecosystem, such as suppliers (through market competition) and consumers (through customer reviews). We find that when suppliers' enforcement is stronger (i.e., the market competition is more intense), the impact of platform disclosure is weaker. Besides, the influence of picture disclosure is impeded when a home cook has a higher hygiene reputation, which is measured by the sentiment of hygiene-relevant comments. Notably, review stars, although easier to obtain, contain limited information on hygiene quality and do not show a significant substitution effect on the platform's hygiene disclosure.

Our work contributes to the literature in several ways. First, it enhances the understanding of how consumers would react to platform disclosed signals in pictures. We highlight an informative effect (which delivers the suppliers' heterogeneous quality), and a qualification effect (which shows the suppliers' competence), that influence consumers' decisions. By showing that the informative effect outweighs the qualification effect and that suppliers with lower quality can suffer a sales decrease from the picture disclosure, our work extends the previous literature, which emphasizes only the positive impact of platform-disclosed badges or pictures. Second, we show that it is the perceived quality that influences the consumers' decision-making process. As the quality signal delivered through pictures can contain noise, it may prevent the most efficient market outcome by influencing the consumer's perceived quality. Third, our study shows how different quality-enhancing mechanisms, such as reputation (through customer reviews) and market competition, interact with platform disclosure. As the three mechanisms naturally correspond to enforcement from the consumer, supplier, and platform sides, our work integrates the enforcement methods from the main parties in the sharing economy ecosystem.

Our work can also benefit the practitioners with their decisions. First, we suggest that the platform can launch a pilot disclosure to identify which suppliers are influenced and adapt the disclosure strategies based on its objectives, such as motivating medium type suppliers or encouraging quality improvement of all suppliers. Second, our work can help the platform owner to allocate inspection resources properly and inspect the suppliers who are most responsive to the disclosed quality signal. Third, the computer-vision and deep-learning techniques applied in the study can be extended to both research and business practice in other areas, such as the hotel, travel, and real estate industries, by automating the image selection procedure and by measuring the image quality based on the overall picture layout.

3.1 SETTING

We conduct the analysis on a home-cooked food-sharing platform. The suppliers are home cooks willing to cook in their home kitchen and share with others. The consumers can be any registered user in the local city. The platform was first established in Beijing in October 2014 and is now the largest home-cooked food-sharing platform in China.

3.1.1 *The Food Sharing Platform*

The platform can be considered a combination of the sharing economy and the restaurant industry that connects home cooks (food suppliers) with consumers. A typical exchange consists of the following steps. First, a home cook uploads the dish details, including dish name, description, image, price, and daily stock to his kitchen. Second, a consumer, given a list of home cooks in her neighborhood (as shown in Figure 3.1a), selects one based on the home cooks' past performance and other demographic information. She then chooses any available dishes from the selected home

cook and places an order (as shown in Figure 3.1b). Third, the selected home cook prepares the ordered dishes. Finally, the consumer receives the food and may leave a review after consumption.

Consumers can evaluate a supplier’s quality based on the online information such as customer reviews and the number of orders the supplier completed in the previous month. However, they still suffer from a lack of offline information, especially hygiene information, because home cooks do not have physical stores. Besides, as home cooks are not professional restaurant owners, they are less likely to have the license required to serve in a restaurant. The lack of licensing procedure and offline hygiene information can add to the uncertainty about home cooks’ hygiene quality.



Figure 3.1 Dish Order Interface

3.1.2 Hygiene Inspection and Result Disclosure

A concern about hygiene risk can prevent customers from engaging in the platform, which hurts the performance of both the supplier and the platform. The uncertainty on the hygiene quality also triggers the consumers’ need for hygiene information. Therefore, the platform started on-site hygiene inspections of the home cooks in December 2016. Below we detail the platform’s inspection procedure and the corresponding disclosure strategy.

First, the platform identifies a set of active home cooks who have not been inspected and need to undergo inspection.⁶ The platform is not concerned with inactive home cooks due to their limited

⁶ Home cooks who have been inspected already will be revisited 3 months later rather than on a random base.

influence on the platform's performance. Second, the platform selects randomly from the active home cooks every week and send inspectors to conduct an on-site inspection. The inspector follows clear guidelines that consist of 31 items, each of which is scored, to evaluate a home cook's hygiene quality. The inspection items fall into three categories: home cook's hygiene habit, hygiene of the kitchen, and hygiene and condition of cooking facilities. The inspector checks each item and takes photos inside the kitchen to track the inspection procedure. After inspection, the inspector will come up with a hygiene grade based on the performance. Home cooks with hygiene grades no lower than C are considered "qualified", while those with hygiene Grade A or B are considered satisfactory. The ones with Grade D will be forced to leave the platform. The inspection results, including the itemized performance, are available to the home cook immediately after the inspection. Appendix A provides a sample of the hygiene inspection report.

The platform does not, however, disclose the inspection results to the public immediately after inspection. Instead, the platform held the results until March 8, 2017, hereafter the "disclosure date", prior to which the inspection information was private to each home cook.⁷ After the disclosure date, the platform released the results of all inspected home cooks by disclosing kitchen pictures.⁸ As shown in Figure 3.2, instead of showing a qualification badge that a home-cook has passed the hygiene inspection, the platform discloses the kitchen pictures taken during the inspection procedure so that consumers not only know that the kitchen is qualified, but can also evaluate the hygiene quality based on the kitchen's condition. Notably, we have learned from the platform that only the picture that best describes the overview of a kitchen, which is often a frontal view, will be selected, as these pictures are more informative.

⁷ Our analysis focuses on the home cooks that are inspected before the disclosure date, and all inspected home cooks in the analysis have been inspected only once.

⁸ The platform does not disclose the results of home cooks with hygiene Grade D, as they are no longer visible to consumers. This group of home cooks comprises 4.05% of all inspected suppliers.

This disclosure strategy relates to the traditional method, which uses a badge to distinguish the suppliers, by providing a qualification signal. Specifically, the kitchen’s picture is a “badge” – the supplier with the picture disclosed are qualified after the hygiene inspection. Thus, this disclosure method poses a qualification effect as the traditional method does. However, it extends the previous practice by delivering additional information through pictures. For instance, a kitchen’s picture is more illustrative and provides more details on a supplier’s hygiene quality than a badge. This way, consumers can better evaluate the heterogeneous hygiene quality through pictures. We refer to the picture’s impact by showing additional information as an informative effect.

The informative effect also depends on how customers would consume and comprehend the picture information. One concern is that consumers may consider it costly to investigate the picture, and consequently, they may react homogeneously to all inspected suppliers, neglecting the details from kitchen pictures. Another concern is that the quality signal through pictures can contain noise. For instance, the picture may not contain all aspects evaluated during the inspection procedure, and consumers’ perceived quality may be different from the platform evaluated quality.



Figure 3.2 Inspection Information Disclosure

Given the unique characteristics of the disclosure strategy, we address the following questions. First, to what extent is the disclosure strategy effective in influencing the consumer’s decision and the supplier’s performance? Second, how does the impact vary for home cooks with different hygiene quality? As the inspection picture disclosure is a newly adopted method to promote

hygiene quality, we also examine how its impact is influenced by other pre-existing quality-enhancing mechanisms, such as reputation and market competition.

3.2 DATA

We first collected the transaction information of home cooks in Beijing during the two-month period of February 6 to April 8, 2017. We then collected the complete inspection history. For each inspection, we have the inspected home cook’s hygiene grade and a set of photos taken during the inspection. By combining the inspection record with the home cook’s transaction data and controlling for other factors, we can compare the difference in performance between the inspected and uninspected home cooks. In what follows, we detail the setting-specific variable construction based on inspection images, consumer comments, and dish images.

3.2.1 *Inspection Images*

The main difference between our setting and other disclosure strategies is that the inspection results are disclosed through images. To exploit the image information, we first identify the disclosed images from all images provided, then construct the perceived hygiene grade from the images.

Recall that, when the platform sends out inspectors to a home cook, the inspector takes about 10 to 20 pictures for the record. We provide examples of the inspection images in Figure 3.3, which shows a frontal view of the kitchen, the sink, a pail of soybean oil, and the interior of the refrigerator. We learned from the platform that the disclosed images are manually selected based on how thoroughly the images show the overall layout of a home cook’s kitchen. Unfortunately, the data do not indicate which images are disclosed. Instead of manually going through thousands of pictures to find the disclosed images, we automate this process by combining deep-learning and computer vision methods to help identify the images that best describe a room or a kitchen’s layout.

We believe that this layout detection procedure is more scalable and can benefit other research as well. Below, we detail the methods applied for room layout detection.



Figure 3.3 Examples of Inspection Images

Room layout estimation from a monocular image has recently received great attention from computer-vision applications. Coughlan and Yuille (2001) first introduced the “Manhattan world assumption” that most indoor and outdoor scenes fall into a three-dimensional grid. Figure 3.4 shows a list of possible room layouts that cover most of the situations under typical camera poses and common cuboid representations under the assumption (Lee et al. 2017, Zhang et al. 2016). Our goal is to train a deep-learning model and predict the layout and key-points of each image.

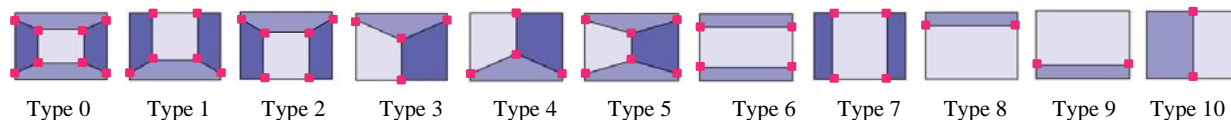


Figure 3.4 Definition of Room Layout Types

As illustrated in Figure 3.4, certain room layouts, such as Type 0, are more likely to represent a frontal view of a room. In Figure 3.5, we provide two examples to help visualize the room layout. The first column is the original image. The second and third columns show boxy room layout representations with a corner representation and a segmentation representation, respectively. Comparing the two sets of pictures, we find that Type 3 better represents a room’s layout, with two wall segments and a ceiling segment. Following this logic, we define the frontal view as a layout that has a floor segment, at least two upright wall segments, and a preferable ceiling segment.

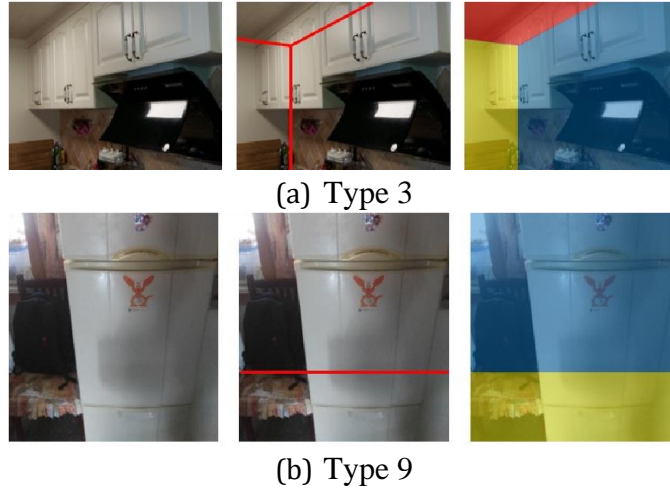


Figure 3.5 Illustration of Room Layout Types (Type 3 and Type 9)

We implemented the recent development of RoomNet based on deep convolutional neural networks. The network architecture is summarized in Figure 3.6. The input to the network is a single RGB 320×320 image, and the output of the network is a set of 2D key-points in a specific order with an associated room type. It consists of an encoder network and a corresponding decoder network, augmented by a side head with fully connected layers to the bottleneck layer for room-type prediction. The detailed functionality and construction of the encoder and decoder subnetwork, as well as the corresponding optimization objective, are demonstrated in Appendix B.

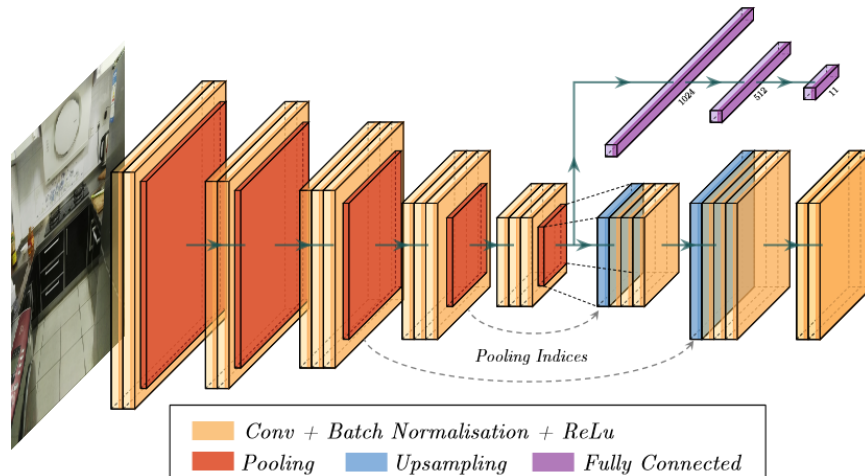


Figure 3.6 An Illustration of the RoomNet Architecture

We trained our network from scratch on the large-scale LSUN dataset (Yu et al. 2015),⁹ and then apply the trained RoomNet on our inspection images to predict their layout. The final output of our automated process is a frontal view image of each home kitchen. Figure 3.7 provides a couple of examples of the results. The first row is the input images, and the second row is the predicted keypoint heatmap generated by connecting predicted key-points. In this set of pictures, the second and the last images are selected as the frontal views.



Figure 3.7 The RoomNet Predictions of Kitchen Layouts

We then construct users' perceived hygiene quality, using the images identified from the previous step. Because the interpretation from an image is subjective, we use Amazon Mechanical Turk (AMT) to construct the perceived hygiene quality based on individuals' annotation. Although individuals' interpretations from an image can be heterogeneous, a large-scale annotation helps to provide a consistent measure of interpretation on an aggregated level.

We use two survey designs to collect the users' perceived hygiene quality from the images. In the first section, users are given one kitchen picture and a set of questions to evaluate hygiene quality from various aspects, such as food storage and condition of utensils. In the second section, users are given nine images and are required to categorize them into three hygiene grades. To

⁹ The results from the training set are presented in Appendix B.

ensure that the results are representative and of reasonable quality, we restrict the sample to workers who are familiar with closed kitchens (i.e., the kitchen layout in the picture) and premium ones with more than 500 approved tasks on AMT. We exclude the tasks completed in less than 60 seconds, as the average processing time per task is around 120 seconds. We also examine the difference in the perceived hygiene grades collected in the two sections and find no significant difference across the two groups. This provides further evidence that the results collected are convincing and consistent. The design of the AMT survey and the test of result consistency are presented in Appendix C. For each kitchen image, we collected, on average, 34 perceived hygiene grades from the second section and calculated the mean of the collected hygiene grades. We categorize the images into the hygiene group whose benchmark grade is the closest to the mean of perceived grades.

3.2.2 *Customer Review*

Similar to other sharing-economy platforms, consumer feedback, such as a review rating, is often used to measure a supplier's quality. The review rating by itself, however, may not fully convey a consumer's attitude. For instance, "The dish tastes good, but I found a hair in it," expresses a positive feeling about the flavor but a negative one for hygiene quality. Notably, a conflicting attitude cannot be reflected using review ratings only.

To disentangle a consumer's attitude toward hygiene quality, we extract hygiene-specific sentiments using the consumers' comments and a set of platform predetermined comment labels from which consumers can select (e.g., "healthy food," "friendly supplier"). Following the opinion-mining method proposed by Hu and Liu (2004), we extract the hygiene-based attitude through the steps below. First, we collect a set of base words (nouns and adjectives) that appear frequently in the comments attached to hygiene-relevant labels. We then apply word-embedding

methods to find words with similar meanings to extend the base words and use the set of extended base words to identify whether a sub-sentence (i.e., sentence parts separated by comma) contains the hygiene relevant topic. We then apply Vader sentiment analysis, a lexicon and rule-based method to extract the sentiment of the hygiene-relevant sentences (Hutto and Gilbert 2014). We measure the hygiene sentiment of a home cook i at period t using the hygiene sentiment variable Hyg_Sent_{it} , the cumulative average of the sentiment of sentences that contain hygiene keywords up to period t .

3.2.3 Dish Information

The food suppliers provide home-cooked meals through the platform. Thus, the dishes that they offer, unlike those served in restaurants, do not necessarily fall into a specific cuisine type, such as Cantonese or Sichuanese. Not surprisingly, neither the suppliers nor the platform provide a clear cuisine type. Home cooks, however, may indeed have preferences for the dishes they provide. We therefore make use of the dish image posted on the platform to describe the dish style.

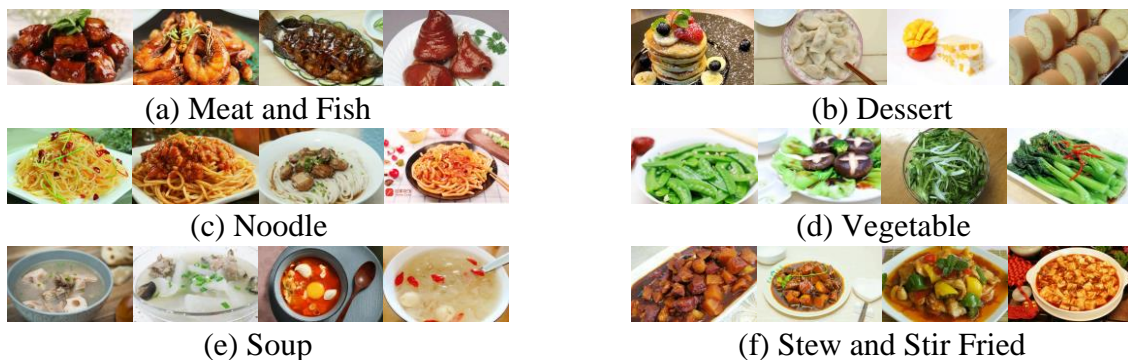


Figure 3.8 Dish Styles after Categorization

We adopt the Inception-V4 deep neural network for image feature extraction. The Inception-V4 model is the state-of-the-art deep structure for image classification and semantic understanding as well as extraction of latent signals from complex images (Szegedy et al. 2017). We use the spatial average of the mixed_7d layer, a 1536-dimension real-valued vector, as the dish image

representation. We then apply k -means clustering approach to categorize the dishes using the features extracted. We characterize the results into six groups: meat and fish, dim sum and desserts, stir-fried and stews, noodles, vegetables, and soups. Figure 3.8 shows four dish images for each dish style. A home cook can provide dishes from multiple styles. We then aggregate the dish style to the home-cook level for each day and construct two variables: (1) dish style proportion, DSH_PCT_{it} = Dish Count in Style j on day t / Total Dish Count on day t , and (2) the majority dish style, DSH_SYL_{jt} , a set of binary variables that indicate whether style j has the most dishes offered on day t .

3.2.4 Other Features

Apart from the features described above, we also include other variables that may correlate with the home cook’s performance. Specifically, we focus on three sets of variables: (1) home cooks’ time-invariant features, including location, delivery radius, delivery fee, and the chef’s gender and age; (2) dish information, including dish variety, stock, and price; and (3) operating features, including coupon value, past transactions, and consumer review stars. Table 3.1 provides a summary of these variables. The features extracted from image and text information are presented in Appendix D.1 and D.2.

Table 3.1 Variable Description and Summary Statistics

Variable	Description	Min	Max	Median	Mean	S.D.
<i>(1) Home Cook Features</i>						
MALE	=1 if chef is male. =0 if chef is female	0.00	1.00	0.00	0.31	0.46
AGE	Home cook’s age	25.00	65.00	45.00	47.03	11.52
CAN_PKP	=1 if pickup is available. =0 if unavailable	0.00	1.00	1.00	0.81	0.39
CAN_DEL	=0 if delivery is available. =0 if unavailable	0.00	1.00	1.00	0.99	0.08
DEL_RDS	Delivery radius in kilometers	0.50	10.00	2.50	2.73	1.36
DEL_FEE	Delivery fee per order	0.00	5.00	2.00	2.39	0.66

(2) Operating Features

Rev	Log transfer of home cook's revenue	0.00	9.61	3.33	2.74	2.77
NetRev	Log transfer of (sales net redeemed coupon)	0.00	9.60	3.22	2.69	2.73
ORD_CNT	Log transfer of home cook's transaction	0.00	5.07	0.69	0.89	1.03
DSH_SLD	Log transfer of dishes sold	0.00	6.30	1.10	1.43	1.55
PST_CSM	Cumulative number of past customers	0.00	9.18	6.01	5.75	1.59
RVW_STR	30-day rolling average of review ratings	1.00	5.00	4.93	4.87	0.23
RVW_CNT	=1 if cumulative review ≥ 90 , =0 if cumulative review < 90 .	0.00	1.00	1.00	0.81	0.39
CPT_INSP	Competition from inspected home cooks	0.00	0.16	0.06	0.06	0.03
TENURE	Home cook's tenure in weeks	0.00	130.00	45.00	48.03	26.99

(3) Dish Features

DSH_PRC	Average price of dish offered	2.35	4.41	2.84	2.91	0.35
CPN	Average coupon redeemed per order	0.00	25.50	3.41	3.98	3.06
DSH_STK	Log transfer of average stock per dish	0.76	4.59	2.14	2.22	0.58
DSH_CNT	Log transfer of dishes offered	1.10	5.81	3.71	3.62	0.73
DSH_SPC	=1 if spicy dish is offered =0 if no spicy dish is offered	0.00	1.00	0.00	0.48	0.50

a) *Time varying features are aggregated to daily level.*

b) *Performance measures equal to zero if no orders are realized.*

c) *CPT_INSP = Inspected home cook count / Total Transaction Count, is calculated for each location and majority dish style*

3.3 MODEL

To investigate the impact of the inspection disclosure, we apply the DiD approach, which is widely used to identify the average treatment effect (Bertrand et al. 2004, Heckman et al. 1998).

3.3.1 *Difference-in-Differences Analysis*

We first describe the treatment assignment of home cooks. Inspected home cooks with their kitchen images disclosed are considered the treatment group. Their inspection results, disclosed in

the form of kitchen images, are unavailable to consumers before the disclosure date but available afterward. Uninspected home cooks are considered the control group, as their kitchen images are not available throughout the period of interest. An important assumption for applying the DiD method for causal interpretation is that the treatment and the control group are comparable such that individual samples of home cooks can be considered to be randomly assigned into the two groups.

In our setting, the randomness of assignment can be influenced in two ways. First, the platform's inspection strategy indicates that the assignment of treatment depends on whether the home cook is active and, thus, the assignment is not ideally random. One case that can potentially lead to a biased estimation occurs when the performance of the control group does not change much after the disclosure date, not because the effect of the inspection disclosure is marginal for the control group but, rather, because a home cook is no longer active on the platform and would not react to the disclosure strategy, regardless of the group to which he or she is assigned. To prevent the bias brought by the inspection strategy, we need to address the potential difference in the active level. Second, because the inspection results are shown to the home cooks immediately after the inspection, yet not available to the customers until the disclosure date, the home cooks can make changes in product quality or daily operating procedures after the inspection but prior to the disclosure date. Therefore, it also is important to control for time-varying features to address the home cooks' potential behavior change over time.

3.3.2 *Propensity Score Matching Method*

To address the issues above, we match the home cooks in pairs so that the inspected and uninspected ones are comparable after the match. We use $ACTIVE_i$, the number of days with valid transactions within a month to measure the active level, as a home cook with no transactions for a

long period of time does not play a major role on the platform. We then use three types of time-varying features to control for the potential behavior change: (i) RVW_STR_i , the average review stars; (ii) PST_REV_i , the logarithm transfer of total sales in the past month; and (iii) DSH_PCT_{ij} , the proportion of dish style j provided among all dishes by home cook i . We use a home cook's tenure in weeks to control for the influence of the business cycle. We also include each home cook's location (determined by ZIP code) to control for its potential influence on the inspection decision.

We apply propensity score matching (PSM), a method used in various fields to obtain random assigned treatment and control groups (Abadie and Imbens 2006, Imbens 2000, Lechner 2001), to conduct the match. This method constructs matched pairs based on the propensity score, the probability for an individual sample to receive treatment, which is expressed as:

$$e(x_i) = P(Treat_i = 1 | X_i)$$

where X_i represents the features described above, and the propensity score is obtained through a probit model. We use nearest-neighbor method and construct a one-to-one match without replacement. The tolerance of the matching score is specified to be 0.01.

After matching, we obtain 212 treated home cooks and 212 controlled counterparts. Figure 3.9 shows the distribution of the propensity score. We find that the distribution of the control group is similar to that of the treatment group. The results indicate that the two groups have the same probability to receive the treatment and that the overlap assumption is satisfied.

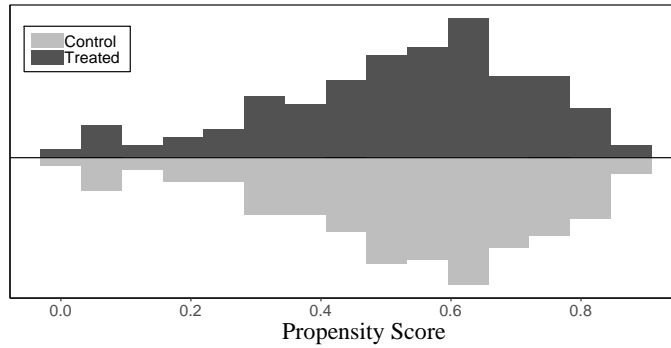


Figure 3.9 The Distribution of Propensity Score

To further test if the matching procedure is valid, we construct balance check on the observed variables. Table 3.2 shows that after match, there is no significant difference between treated group and matched control group. This provides evidence that if observable features capture all information of a home cook, the assignment of matched samples can be considered to be random.

Table 3.2 Balance Check

<i>Probit Model</i> <i>Features</i>	Before Match				After Match			
	Mean		t-test		Mean		t-test	
	Control	Treatment	t	p-value	Control	Treatment	t	p-value
RVW STR	4.880	4.840	2.570	0.010	4.860	4.840	0.834	0.404
TENURE	39.430	50.720	-6.960	0.000	43.211	40.023	1.221	0.223
ACTIVE	12.410	20.690	-13.850	0.000	17.704	17.967	-0.305	0.760
PST REV	6.180	8.280	-14.200	0.000	7.836	7.845	-0.077	0.939
<i>Other Features</i>								
AGE	47.994	49.138	1.638	0.102	48.502	48.925	0.382	0.703
GENDER	0.306	0.317	-0.420	0.675	0.296	0.352	-1.242	0.215
CAN PKP	0.807	0.834	-1.133	0.258	0.817	0.817	0.000	1.000
CAN DEL	0.986	1.000	-2.520	0.012	0.995	1.000	-1.000	0.318
CPT INSP	0.049	0.072	-14.105	0.000	0.070	0.072	-1.448	0.148
RVW CNT	0.643	0.901	-10.249	0.000	0.779	0.826	-1.270	0.224
CPN	4.212	4.566	-1.592	0.112	4.392	4.516	-0.358	0.721
DSH PRC	28.039	24.865	2.553	0.011	25.980	24.548	1.325	0.186
DSH STK	2.206	2.281	-2.103	0.036	2.194	2.253	-1.021	0.308
DSH CNT	3.484	3.783	-6.849	0.000	3.690	3.594	1.470	0.142
PST CSM	2.833	4.492	-16.764	0.000	3.926	3.996	-0.589	0.556

Note: The set of location dummy and dish type percentage are balanced after matching

3.3.3 Model Specification and Results

We then apply the DiD approach to the matched sample to identify the causal effect of the inspection disclosure on the inspected home cook's performance. Our model is specified as:

$$\begin{aligned} Rev_{it} = & Intercept + \beta_1 Treat_i + \beta_2 AFT_t + \beta_3 Treat_i \cdot AFT_t \\ & + \beta_4 Rev_{it-1} + \gamma Controls_{it} + \alpha_i + T_t + \varepsilon_{it} \end{aligned} \quad (1.1)$$

where $Treat_i$ equals 1 if a home cook belongs to the treatment group, and 0 if he belongs to the control group. AFT_t equals 1 if time period t is after the disclosure date, and 0 otherwise. Let $Disclosure_{it} = Treat_i \cdot AFT_t$. Then $Disclosure_{it}$ equals 1 if home cook i has been inspected with the image disclosed in a time period t after the disclosure date, and 0 otherwise. We control for Rev_{it-1} , the home cook's revenue in the previous time period. $Controls_{it}$ represents the other control variables that potentially correlate with sales. We include a home-cook fixed effect (α_i) to control for time-invariant features, and a time fixed effect (T_t) to control for seasonality and time trend. ε_{it} is a random shock on sales and is assumed to follow a normal distribution $N(0, \sigma^2)$.

Note that, after controlling for the home-cook fixed effect, the time-invariant features can no longer be identified. This includes $Treat_i$ and other time-invariant control variables, such as gender and location. Similarly, after controlling for the time fixed effect, the features that depend only on time (e.g. AFT_t) cannot be identified. Therefore, the model can be rewritten as:

$$Rev_{it} = Intercept + \beta_3 Disclosure_{it} + \beta_4 Rev_{it-1} + \gamma Controls_{it} + \alpha_i + T_t + \varepsilon_{it} \quad (1.2)$$

where $Controls_{it}$ includes only time-varying features. Specifically, we include (1) review information RVW_STR_{it} and RVW_CNT_{it} , (2) home cook i 's historical performance PST_CSM_{it} , (3) price and coupon information DSH_PRC_{it} and CPN_{it} , (4) the home cook's dish availability and style DSH_CNT_{it} , DSH_STK_{it} , DSH_SPC_{it} , and DSH_SYL_{ijt} , and (5) the local market competition

CPT_INSP_{it} . We also include the home cook's tenure. β_3 is the parameter of interest, which estimates the influence of inspection image disclosure on the home cook's sales performance.

A major concern when estimating the two-way fixed effect model directly is the dynamic panel bias, which arises when both fixed effect α_i and a lag term of the dependent variable Rev_{it-1} are included (Nickell 1981). We therefore construct a dynamic panel data model, following the method proposed by Arellano and Bond (1991). We first eliminate the individual fixed effect (α_i) through first-differencing operation, and we have:

$$\Delta Rev_{it} = \beta_3 \Delta Disclosure_{it} + \beta_4 \Delta Rev_{it-1} + \gamma \Delta Controls_{it} + \Delta T_t + \Delta \varepsilon_{it} \quad (1.3)$$

where Δ refers to the first-differencing operation.¹⁰ The OLS estimation for Equation (1.3) can be biased due to the correlation between $\Delta \varepsilon_{it}$ and ΔRev_{it-1} . We address the concern by introducing a series of lag terms of Rev_{it-1} as instrumental variables (i.e., Rev_{it-k} , where $2 \leq k \leq t-1$). As discussed in Holtz-Eakin et al. (1988), these are valid instruments because the performance of two or more periods before the current time period, such as Rev_{it-2} , is not correlated with $\Delta \varepsilon_{it}$ yet is correlated with ΔRev_{it-1} . Note that the intercept is also removed, as it does not vary over time. We are interested in β_3 , which indicates the impact of the disclosure strategy.

Using the matched sample, we apply an ordinary least squares (OLS) approach to estimate the two-way fixed effect model shown in Eq. (1.2) and apply general method of moments (GMM) approach to estimate the dynamic panel data model shown in Eq. (1.3). The estimation result is reported in Table 3.3 Column (a) and (b), respectively. We find that the estimation for the two models are, in general, consistent. Because the estimation through the GMM method addressed the dynamic panel bias issue, we focus on the interpretation for Column (b). Consistent with our

¹⁰ For instance, $\Delta \varepsilon_{it} = \varepsilon_{it} - \varepsilon_{it-1}$, $\Delta Rev_{it} = Rev_{it} - Rev_{it-1}$, and so forth.

intuition, review rating, review count, coupon value, dish variety, and sales performance in the past time period are positively correlated with sales performance, whereas dish price and competition from inspected home cooks are negatively correlated with sales.

Table 3.3 The Impact of Inspection Information Disclosure

Variables	(a) Fixed Effect		(b) Dynamic Panel	
	(1) Controls - OLS	(2) Full - OLS	(3) Controls - GMM	(4) Full - GMM
Disclosure		0.122** (0.049)		0.207*** (0.080)
Rev _{t-1}	0.392*** (0.006)	0.392*** (0.006)	0.251*** (0.007)	0.250*** (0.007)
CPT_INSP	-7.950*** (1.641)	-7.964*** (1.641)	-13.10*** (2.021)	-13.09*** (2.021)
DSH_PRC	-1.067*** (0.078)	-1.065*** (0.078)	-1.244*** (0.098)	-1.237*** (0.098)
CPN	0.009* (0.005)	0.009* (0.005)	0.030*** (0.006)	0.030*** (0.006)
RVW_STR	0.226*** (0.086)	0.219** (0.086)	0.488*** (0.129)	0.479*** (0.129)
RVW_CNT	0.13 (0.109)	0.134 (0.109)	0.308** (0.132)	0.297** (0.132)
DSH_CNT	0.493*** (0.150)	0.499*** (0.150)	0.796*** (0.204)	0.806*** (0.204)
DSH_STK	-0.668** (0.281)	-0.694** (0.282)	-0.381 (0.395)	-0.47 (0.396)
DSH_SPC	0.33 (0.443)	0.355 (0.443)	0.883 (0.658)	0.919 (0.658)
PST_CSM	0.131 (0.103)	0.14 (0.103)	-0.119 (0.117)	-0.099 (0.117)
TENURE	-0.025 (0.043)	-0.025 (0.043)	-0.03 (0.044)	-0.03 (0.044)
Constant	3.323* (1.941)	3.328* (1.941)		
Observations	23,673	23,673	23,570	23,570
Dish Style	-Included-	-Included-	-Included-	-Included-
Home Cook FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. Standard error in bracket

As shown in Column (4), β_3 is positive significant, indicating a positive treatment effect. Specifically, disclosing the inspection image can lead to an average sales increase of 23% for the inspected home cooks. Note that the average sales of an inspected home cook prior to the inspection disclosure is 3073.28 RMB (or approximately \$466) per month and that the estimation result indicates a sales increase of approximately around \$107 per month.

3.3.4 Robustness Checks

In this section, we construct several tests to validate our results, including a falsification test of the common trend assumption and estimation using other performance measures.

3.3.4.1 Falsification test: Common trend

One major assumption to apply DiD approach is that the treatment and the control group share the same trend during the period prior to the treatment time point (Angrist and Pischke 2008). To test whether the common trend assumption is satisfied, we construct the relative time model and include the pre-treatment time periods (Autor 2003). Specifically, the model can be written as:

$$\Delta Rev_{it} = \beta_3 \Delta Disclosure_{it} + Treat_i \sum_j \delta_j \Delta P_{jt} + \beta_4 \Delta Rev_{it-1} + \gamma \Delta Controls_{it} + \Delta T_t + \Delta \varepsilon_{it} \quad (1.4)$$

where P_{jt} is a set of dummies indicating that whether time period t is j periods before the disclosure date. We include three periods prior to the disclosure date (i.e., P_{1t} , P_{2t} , P_{3t}). We set the rest of the prior periods as P_{4t} and use it as the benchmark. If the common trend assumption is satisfied, the difference in the pre-treatment periods should be insignificant.

Following the steps in Section 3.3.3, we apply GMM estimation, and the results are shown in Table 3.4. We find that δ_j is not significantly different from zero. Thus, during the period before the disclosure date, the treatment and the control group share a common trend in their sales.

Table 3.4 Relative-time Model

Variables	Estimates	s.e.
Disclosure	0.124**	(0.051)
$P_{1t} \cdot Treat$	0.004	(0.184)
$P_{2t} \cdot Treat$	-0.010	(0.186)
$P_{3t} \cdot Treat$	0.179	(0.192)
Observations	23,570	
Control Variables	-Included-	
Time FE	Y	

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

3.3.4.2 Other performance measures

Apart from sales revenue, we use a set of other performance measures to examine whether our results remain consistent. Specifically, we include (1) $NETREV_{it}$, the daily net revenue, a measure of net income of a home cook; (2) ORD_CNT_{it} , the daily transactions realized, a measure of overall market demand; and (3) DSH_SLD_{it} , the number of dishes sold per day, a measure of dish demand, as our performance measures.¹¹ The estimated results are shown in Table 3.5. The estimations are positive and significant, indicating that the influence of the inspection disclosure is consistent for other performance measures.

Table 3.5 Impact of Inspection Disclosure on Other Measures

Variables	Net Revenue Estimation	Order Count Estimation	Dish Sold Estimation
Disclosure	0.208*** (0.079)	0.045* (0.026)	0.090** (0.041)
NetRev _{it-1}	0.249*** (0.007)		
ORD_CNT _{it-1}		0.264*** (0.007)	
DSH_SLD _{it-1}			0.258*** (0.007)
Other Controls	-Included-	-Included-	-Included-
Time FE	Y	Y	Y
Observations	23,570	23,570	23,570

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. Standard error in bracket

3.3.4.3 Other robustness checks

We also construct a set of other robustness checks. First, to address the concern about potential heteroskedasticity and the serial correlation within each home cook, we re-estimate our model using robust standard errors. As indicated in Table 3.6 (1), the estimated impact of disclosure remains consistent and significant, suggesting that our finding is robust to heteroskedasticity and home-cook level serial correlation. Second, it is possible that the inspection disclosure does not influence the sales performance immediately. Instead, the impact is reflected in sales performance

¹¹ We apply logarithm transfer to these measures to address the concern of the variables' long-tail distribution.

after a certain period of time. We therefore construct variable $Disclosure_{it-r} = Treat_i \cdot AFT_{t-r}$. An inspected home cook will have $Disclosure_{it-r} = 1$ if time period t is r periods after the disclosure date, and $Disclosure_{it-r} = 0$ otherwise. An uninspected home cook will always have $Disclosure_{it-r} = 0$. We consider a one-day lag and a one-week lag of the impact, with $r = 1$ and $r = 7$, respectively. The estimation is reported in Table 3.6 (2) and (3), indicating consistent findings. Third, we consider removing the impact of seasonality. In addition to including a time fixed effect, we also aggregate our data into weekly level. We then conduct the same analysis described in Section 3.3.3, and the estimation result is shown in Table 3.6 (4). We find that the results remain consistent using a weekly panel.

Table 3.6 Other Robustness Checks

	(1)		(2)		(3)		(4)	
Variables	Heteroskedasticity Estimation		One-day Delay Estimation		One-week Delay Estimation		Weekly Revenue Estimation	
Disclosure _{it}	0.207*	(0.118)					0.225*	(0.131)
Disclosure _{it-1}			0.117**	(0.049)				
Disclosure _{it-7}					0.100**	(0.051)		
Rev _{it-1}	0.252***	(0.015)	0.392***	(0.006)	0.339***	(0.006)	0.069***	(0.018)
Other Variables	-Included-		-Included-		-Included-		-Included-	
Time FE	Y		Y		Y		Y	
Observations	23,570		23,570		23,196		2,793	

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. Standard error in brackets.

For column (4), time period t is defined by week. Thus, Rev_{t-1} indicates the revenue from the prior week

3.3.5 Hygiene Grades and Suppliers' Performance

So far, we have concluded that disclosing the kitchen picture from inspection has a positive impact on the sales. The result is consistent with our intuition, as disclosing the picture indicates that a supplier has met the platform's requirement. However, the hygiene condition can still be different for these home cooks – some insist a high hygiene quality, while some keep the hygiene just about

to pass the inspection. While the objective of disclosing pictures is to help consumers better evaluate hygiene quality, how consumers would consume and react to the quality signal requires further investigation. Recall that two effects can come into play when pictures are disclosed - a qualification effect and an informative effect. If consumers consider it costly to interpret the hygiene quality from pictures and treat all inspected home cooks homogeneously, the qualification effect is stronger. In this case, the suppliers with a lower hygiene quality can free-ride and enjoy the sales increase without putting further effort into improving the hygiene. The ones with high hygiene quality, in contrast, will not benefit as much. This could still result in market inefficiencies, indicating that disclosing pictures can be ineffective. If the informative effect is stronger, on the other hand, consumers will exploit the information from the images, and the strategy is more likely to be effective – suppliers with the highest hygiene grade enjoy the most sales increase, and those with the lowest hygiene grade are not benefited, or even suffer from a sales decrease.

To further examine how users would consume the disclosed picture information, we sub-sample the data based on the platform evaluated hygiene grade that the suppliers receive. We apply the same model in Equation (1.2) on different data sub-samples, whereby the treatment groups are home cooks with hygiene Grades A, B, and C, and the control groups are their matched pairs. The estimation result is shown in Table 3.7 Panel A. First, we find that disclosing kitchen pictures leads to a heterogeneous effect on home cooks' sales performance - the home cooks with a hygiene Grade B enjoy a sales increase, whereas those with a Grade C suffer a sales decrease. Recall that the low type suppliers (i.e., those receive Grade C from the inspection) still passed the inspection and have their kitchen's pictures disclosed. The sales decrease of these suppliers indicates that the low type ones cannot free ride by having its inspection record disclosed. This result also shows that for the two effects we discussed previously, the informative effect outweighs the qualification

effect. If the qualification effect is stronger, consumers will always consider the inspected ones as higher quality, and even the low type ones can benefit from the disclosure strategy, which is not our case. Instead, consumers tend to form up the suppliers' perceived hygiene quality based on the kitchen's picture and adapt their behavior accordingly. If the consumer's perceived hygiene quality after exploiting the kitchen's picture information is lower than the expected hygiene quality before receiving the quality signal, the supplier is likely to suffer from a sales decrease.

Table 3.7 Effect of Heterogeneous Hygiene Grade

<i>Panel A: Platform Labeled Hygiene Grade</i>						
	(1) Grade A		(2) Grade B		(3) Grade C	
Variables	Estimation		Estimation		Estimation	
Disclosure	0.111	(0.106)	0.219***	(0.078)	-0.437**	(0.176)
Rev _{it-1}	0.228***	(0.013)	0.308***	(0.008)	0.376***	(0.020)
Control Variables	-Included-		-Included-		-Included-	
Time FE	Y		Y		Y	
Observations	6,079		15,281		2,210	

<i>Panel B: Perceived Hygiene Grade</i>						
	(1) Grade A		(2) Grade B		(3) Grade C	
Variables	Estimation		Estimation		Estimation	
Disclosure	0.237***	(0.090)	-0.028	(0.078)	-0.364**	(0.158)
Rev _{it-1}	0.253***	(0.011)	0.335***	(0.009)	0.378***	(0.019)
Control Variables	-Included-		-Included-		-Included-	
Time FE	Y		Y		Y	
Observations	8,234		12,798		2,492	

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. Standard error in brackets.

Interestingly, the estimation of β_3 for suppliers with Grade A is smaller than that for Grade B and statistically insignificant. It indicates a non-monotonic influence of sales on hygiene grade and that those with the highest hygiene grade from the inspection do not benefit the most from the disclosure. One explanation for the non-monotonic pattern is that the platform labeled hygiene grade can be different from the consumers' perceived hygiene grade. This difference may arise when the disclosed kitchen pictures, though helpful in showing the difference across the consumers,

do not fully reflect the hygiene quality from the inspection. Recall that a hygiene grade is given based on a list of criteria from multiple aspects, such as food storage, equipment condition, and the hygiene of the layout. The kitchen’s pictures, however, may not cover all aspects. Furthermore, consumers do not have access to the platform evaluated hygiene grade. Consequently, when consumers rely on the picture information to construct the perceived hygiene quality, their perceptions can be different from the platform’s evaluations. The difference can further lead to the non-monotonic impact on the suppliers’ performance and influence the effectiveness of the disclosure strategy.

To further investigate in the non-monotonic pattern, we compare the perceived hygiene grade collected from AMT with the platform evaluated grade. As shown in Table 3.8, 36% of home cooks with hygiene Grade A from the inspection are considered medium hygiene quality (Grade B), while 29% of home cooks with platform evaluated Grade B are considered a higher hygiene grade A. This indicates that the inconsistency between the perceived hygiene quality and the platform evaluated hygiene quality exists. Given such evidence, we re-estimate the model, using sub-samples based on the perceived hygiene grade. If consumers investigate the inspection image and react to their belief accordingly, the estimation result is more likely to show a monotonic pattern.

Table 3.8 Platform Evaluated Grade and Perceived Grade

	Platform Evaluated Grade		
	A	B	C
Perceived Grade A	35	40	0
Perceived Grade B	20	90	4
Perceived Grade C	0	7	16
Upward Bias	0	0.29	0.20
Downward Bias	0.36	0.05	0

As shown in Table 3.7 Panel B, the estimations of β_3 on the sub-samples show a monotonic pattern: Suppliers with a perceived hygiene Grade A enjoy the highest sales increase, and the ones with a perceived Grade C suffer a sales decrease. The performance of those with perceived Grade B is not influenced. The monotonic pattern in the perceived hygiene grade indicates that consumers behave rationally, following their belief in the hygiene quality after exploiting the information from the images. Thus, home cooks with the highest *perceived* hygiene quality enjoy the most significant sales increases. In other words, if the inspection images contain complete information, and the perceived hygiene grade is consistent with the platform evaluated grade, the effectiveness of disclosing pictures may improve and the monotonic pattern is likely to be preserved.

This finding can help with the platform's disclosure decision. If a particular group is more distinguishable from the other groups (e.g., in our case, the Grade C type), the impact on it is more likely to be consistent as the platform's evaluation. Otherwise, the influence can be mixed, given the nature that pictures can contain incomplete information. The platform may want first to launch a pilot disclosure to identify which group is more distinguishable from others, which group may suffer a sales decrease, and which group may hurt purely due to the noise in the images. Then it should carefully specify its objective to adjust the disclosure strategy accordingly. In our setting, for instance, if the platform's objective is to influence only the home cooks with an unsatisfactory hygiene grade (i.e., low type), without demotivating the medium type, the current strategy is appropriate. However, if the objective is to encourage all home cooks to pursue a higher hygiene quality following the inspection rubrics, then it is better to disclose more detailed information in the disclosed pictures, or even directly reveal the platform evaluated hygiene grade.

3.3.6 *Disclosure, Reputation, and Competition*

Given the previous result that disclosing pictures can lead to negative sales impact to the suppliers with relatively low hygiene quality, another way to consider the inspection disclosure is a source of enforcement from the platform side. It is, therefore, natural to investigate how the platform's enforcement interact with other pre-existing enforcement in a sharing economy platform. Other enforcement can come from consumers through review comments and ratings, known as the reputation mechanism, or the pressure of competing suppliers, known as the competition mechanism. In a sharing-economy platform, both competition and reputation are widely applied to encourage satisfactory service quality. In this section, we analyze how platform disclosure interacts with these two mechanisms. This can help us to understand the role of inspection disclosure among the quality-enhancing tools and benefit the platform to make better inspection and disclosure decisions.

3.3.6.1 Competition mechanism

We start from the analysis of market competition, a major mechanism to motivate suppliers to guarantee or improve product quality (Matsa 2011, Mazzeo 2003). When the market competition is intense, it is easier for consumers to switch to a different supplier, and the supplier's quality tends to be higher. Prior studies consider the pressure from the competing peers as "a source of discipline" (Gans 2002, Hart 1983). Following this idea, we frame competition as the enforcement from the supplier side in the sharing-economy platform.

The impact of market competition on platform disclosure can be two-fold. On the one hand, if the market competition is intense, consumers may be more reactive to the platform disclosed information, as the information can better help with the decision process, given more choices on the market. This way, the effectiveness of platform disclosure would be enhanced if the market

competition is intense. On the other hand, suppliers may already have a high hygiene quality to survive in a competitive market, and the extra information offered by the platform disclosure is minimal. If so, the platform disclosure may be less effective when the market competition is intense.

To examine which force is stronger, we analyze how the effectiveness of the hygiene inspection disclosure would be influenced by market competition. The influence can be considered a moderation effect. Thus, we estimate an updated model, as specified below:

$$\begin{aligned} Rev_{it} = & Intercept + \beta_3 Disclosure_{it} + \beta_4 Compete_{it} + \beta_5 Rev_{it-1} \\ & + \beta_6 Compete_{it} \cdot Disclosure_{it} + \gamma Controls_{it} + T_t + \alpha_i + \varepsilon_{it} \end{aligned} \quad (1.5)$$

where $Compete_{it}$ is competition intensity. We use two variables to measure competition intensity. First, we use $Cpt_Ratio_{it} = LocSpl_{it} / LocDmd_{it}$, the ratio of local supply and local demand, where $LocSpl_{it}$ and $LocDmd_{it}$ are the number of active home cooks in i 's district on period t and the number of orders completed i 's district on period t , respectively¹². If Cpt_Ratio_{it} is higher, competition is more intense. Second, we consider HHI_{it} , the Herfindahl-Hirschman index (HHI , for short) that measures the market concentration and is widely applied in the literature, as a proxy for market competition (e.g., Mazzeo 2003). It is worth noting that a higher HHI indicates a higher market concentration or, equivalently, a lower market competition. Similar to the main model, we conduct GMM estimation, and β_6 is the parameter of interest.

As shown in Table 3.9 (a), the estimation for β_6 is negatively significant for Cpt_Ratio and positively significant for HHI , indicating that consumers are less likely to react to the disclosed pictures when competition intensity is high or when market concentration is low. This result

¹² District is measured by the ZIP code and is used to define the local market. This method is commonly applied in various fields because the ZIP code is easy to access and performs well in capturing geographic closeness.

suggests that in a competitive market, force to mitigate the impact of platform disclosure on hygiene quality outweighs the force to enhance it, probably because the overall hygiene quality is high in the market, and the disclosed pictures provide very limited extra information. Therefore, the impact of platform side enforcement is attenuated when market competition is high. The result can also benefit the platform decisions. Specifically, given the limited workforce to conduct the on-site inspection, the platform should prioritize the home cooks who are located in less competitive areas to exploit the value of the inspection disclosure.

Table 3.9 Platform Disclosure and Other Mechanisms

Variables	(a) Competition		(b) Reputation	
	(1) Compete Ratio	(2) HHI	(3) Review Star	(4) Hyg Sentiment
Cpt_Ratio · Disclosure	-2.419*** (0.842)			
HHI · Disclosure		9.068** (4.537)		
RVW_STR · Disclosure			-0.036 (0.141)	
Hyg_Sent · Disclosure				-0.201* (0.107)
Disclosure	0.443*** (0.160)	-0.054 (0.093)	0.295 (0.687)	0.451** (0.183)
Rev _{it-1}	0.274*** (0.007)	0.274*** (0.007)	0.398*** (0.006)	0.398*** (0.006)
Observations	23,570	23,570	23,570	23,570
Other Controls	-Included-	-Included-	-Included-	-Included-
Time FE	Y	Y	Y	Y

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. Standard error in brackets.

3.3.6.2 Reputation mechanism

We then investigate the role of the reputation mechanism, which is widely adopted by the sharing-economy platforms, through a review system. The customer review provides a quality signal of a supplier and can help to prevent opportunistic behavior. It thus can be considered enforcement from the consumer side. The reputation mechanism is similar to the competition mechanism - one would perceive that suppliers with higher review ratings or review comments have higher product quality. We consider two measures for reputation: review rating, representing a supplier's overall quality of product and service, and the consumers' attitude toward hygiene quality extracted from

their comments, representing the hygiene-specific reputation. We apply a model similar to the competition mechanism, as shown below:

$$\begin{aligned}
 Rev_{it} &= Intercept + \beta_3 Disclosure_{it} + \beta_4 Reputation_{it} + \beta_5 Rev_{it-1} \\
 &+ \beta_6 Reputation_{it} \cdot Disclosure_{it} + \gamma Controls_{it} + T_t + \alpha_i + \varepsilon_{it}
 \end{aligned}
 \tag{1.6}$$

The results are shown in Table 3.9 (3) and (4). The estimation is negatively significant for hygiene-specific reputation yet insignificant for reputation described by review stars. Recall that the hygiene-specific reputation is obtained through aspect-based sentiment analysis that identifies the sentiments towards hygiene quality. This result indicates that the reputation mechanism has a substitution effect on the impact of platform disclosure only if it is specific to hygiene quality and that the review rating provides limited information about a home cook's hygiene quality.¹³ Given such a result, the platform owner, instead of using review ratings to measure a home cook's hygiene quality, should apply text-mining techniques and exploit information from consumer comments to better target the home cooks to inspect.

One potential concern for the analysis is the selection by reputation and competition. If the platform strategically selects home cooks with worse (better) reputation located in more (less) competitive regions, then the estimation would be biased. We construct a balance check of these variables to address the issue. The results of the balance check are reported in Appendix D.4.

3.4 DISCUSSION AND CONCLUSION

The sharing economy has been experiencing tremendous growth in recent years. The peer-to-peer nature of the sharing economy, when accepting nonprofessional suppliers, raises concerns about information asymmetry. Platform information disclosure, a method to alleviate the information

¹³ Using the sentiment from the entire comment content without specifying the hygiene-specific sentiment performs similar to review ratings. The results are included in Appendix D.3.

asymmetry by providing quality signal, is broadly applied in the sharing economy platforms. For instance, many platforms choose to endorse a badge to help consumers identify the suppliers that meet specific criteria. However, this method provides limited information on the suppliers' heterogeneous quality over a spectrum (e.g., high, medium, low quality).

Recently, platforms started to use pictures as quality signals. Although images are more illustrative than badges, consumers may consider it costly to extract information from these pictures and still treat all images as a homogeneous quality certificate. Even with sufficient effort, consumers need to balance the qualification effect and the informative effect. The effectiveness can also be influenced by how well a picture can match with the inspection rubric and other mechanisms in the sharing economy to enforce the supplier's quality.

Using a data set from a meal-sharing platform in China, we find that disclosing the platform's hygiene inspection picture, on average, improves suppliers' sales performance by 23%. Despite the overall sales increase, suppliers with low hygiene quality suffer from a sales decrease. Besides, the impact on suppliers' performance is non-monotonic in terms of their platform evaluated hygiene grade but monotonic in terms of consumers' perceived hygiene grade. This indicates that consumers tend to exploit the picture information upon making decisions and that the impact of information through pictures outweighs the qualification effect. In the meantime, although consumers tend to exploit inspection information, the inconsistency between the picture information and the hygiene inspection details could lead to the consumers' misinterpretation of the hygiene quality. Consequently, suppliers with high hygiene quality may not benefit from the unstructured disclosure.

We also investigate how other quality-enhancing mechanisms interact with the platform disclosure strategy. We find that the effectiveness of platform disclosure is attenuated when market

competition is intense. Besides, the reputation mechanism substitutes for the impact of the platform disclosure, while the substitution effect is significant only when it is specific to hygiene quality.

Our work contributes to the literature by analyzing the impact of picture disclosure on consumer decisions. Previous studies focus on the positive role of pictures where suppliers with professionally taken photos enjoy a demand increase due to some specific image characteristics. In earlier research, photos are either disclosed with highlight marks or taken by professionals that make them visually more attractive. Thus, these studies often find revealing pictures beneficial to suppliers. We, however, focus on the significance and importance of the informative role of photos. In our setting, pictures come from the inspection process, without intentional manipulation to make images more appealing. By showing the negative impact of disclosing the image of a supplier with a qualified but relatively low hygiene quality, we emphasize that images that appropriately describe the suppliers' quality can lead to more effective outcomes - consumers tend to exploit image information, and the informative role overweighs the qualification role. Therefore, if consumers find that a supplier's perceived quality inferred from the picture is lower than their expectation (i.e., the prior belief of quality before disclosure), they are likely to switch to other suppliers, and the supplier will suffer from a sales decrease. The negative influence on the performance can motivate the supplier to improve the quality if the cost of improving quality is lower than the sales decrease. Furthermore, we emphasize that though informative, pictures carry incomplete quality information, and consumers' choices may not align perfectly with the platform's evaluation. The inconsistency can arise when the quality inspection contains detailed rubrics, but pictures do not cover all of them. One can also consider the disclosure as enforcement from the platform side. As customer review and market competition naturally correspond to

enforcement from the consumer and supplier side, we investigate the role of platform side enforcement in the sharing economy ecosystem.

From a practical point of view, our work also provides guidance to platform owners in terms of inspection and disclosure strategies. Practitioners can start by making inspection decisions more wisely. For instance, to better allocate limited regulation resources and budgets, the platform can first target suppliers in an area with less intense competition. Similarly, it can prioritize the inspection of the suppliers with a poor reputation. Notably, if the platform is interested in a specific aspect (e.g., in our case, hygiene quality), it is more proper to measure reputation using the customer's comment on the particular topic than using the review ratings. Upon disclosure, the platform may want to conduct a pilot launch to identify the impact of noise in pictures, if there is any. It can then decide the formal disclosure strategy (e.g., who and how to disclose) based on its objective, such as encouraging medium type, improving quality, and rewarding high type.

Technically, our analysis integrated text-mining, computer-vision, and deep-learning techniques with the econometric model to help better understand the influence of different types of information in the sharing economy. We show the method and the value of applying topic-specific text information in the firm's decision procedure. Further, the computer-vision and deep-learning techniques applied in our work can be implemented in business practices in the real estate, travel, and hotel industries. These techniques can help to automate the image-selection procedure and to reduce the corresponding labor cost. The method can also be applied in future research that involves image mining for either data preprocess and filtering or the evaluation of image quality from the perspective of layout and room structure.

Our study can be extended in several ways. Due to data limitations, we assume that consumers are aware of the inspection results after disclosure. In reality, only some consumers might be aware

of the inspection results, while others are not. The model can be refined if detailed information about who observes the inspection results become available. Besides, our study analyzes the platform's picture disclosure when government disclosure is not available. If government disclosure is available, future research could consider comparing government disclosure and platform disclosure to examine their relative and interactive impacts.

Chapter 4. INFLUENCE OF PEER-BASED MONETARY INCENTIVE ON CONTENT GENERATION: EVIDENCE FROM A SOCIAL MEDIA SITE

The value of user-generated content has received significant attention in the past years. Platforms that rely on user-generated content (UGC) platforms have achieved enormous success. Reddit, a social content-sharing platform, has over 430 million monthly active users, providing over 21 billion monthly screen views.¹⁴ YouTube, a video-sharing platform, achieved an advertising revenue of \$15 billion in 2019.¹⁵ Interestingly, content consumers on these platforms can get access to news, obtain knowledge, and enjoy video clips without monetary payment – the platform usually earns profit through advertisement and optional subscription fees.

The success of these platforms relies heavily on the high-quality contents, which not only keeps users engaged, but also attracts higher traffic and greater profit. The production of those contents depends on the contribution of content generators, the users on the platform who put effort into writing posts, sharing knowledge, and creating video clips. Therefore, motivating content generators could be a critical issue for the UGC platforms.

Despite the significance of high-quality content, the approaches applied to motivate content generators remain limited. Content generators often receive non-monetary rewards, such as likes, upvotes, or comments from content consumers in return for producing the valuable content. Recently, some platform starts to search for new channels to motivate the content generators, such as rewarding content generators with trophies or badges.¹⁶ However, content generators are still unable to collect monetary revenue through these methods, and the benefit remains as the feeling

¹⁴ <https://www.redditinc.com/>

¹⁵ <https://www.businessinsider.com/youtube-ad-revenue-15-billion-2019-google-breakout-2020-2>

¹⁶ <https://www.reddit.com/wiki/trophies>

of doing good and sharing their knowledge and experience. Consistent with the business practice, researchers also tend to emphasize the importance of social capital gain and positive public image in motivating the content generation behavior (Hennig-Thurau, 2004; Shen et al. 2015; Lerner and Tirole 2002; Daugherty et al. 2008).

Content generators, on the other hand, might be willing to receive the monetary reward, and some are actively searching for approaches to monetize their content and popularity. For instance, some popular streamers on Twitch choose to monetize their content value by signing contracts with the platform and provide quality content at a stable rate.¹⁷ Content generators on other platforms may monetize their popularity by posting advertisements on the platform. The need for monetary reward indicates that it can be a potential method to incentivize the content generators for content production. However, the monetizing tools mentioned above are often available to only a limited number of star users, leaving the majority of the content generators unbenefited.¹⁸

In recent years, some practitioners have realized the concern of a lack of monetary reward and have started to involve monetary incentives to motivate the content generation process. For instance, WeChat, an instant messaging app that allows for article sharing, enables readers of an article to “reward” the writer through money transactions. Himalaya Media, an audio content production platform based in San Francisco, allowed users to “tip” the podcast creators through their apps.¹⁹ These business applications share two characteristics. First, it is the content consumers, rather than the platform, that provide the monetary incentive. Therefore, the monetary incentive is “peer-based”. Second, the reward is offered in the form of “tips”, indicating that the

¹⁷ <https://www.twitch.tv/partner/signup>

¹⁸ <https://www.businessinsider.com/money-youtube-stars-actually-make-2014-2>

¹⁹ <https://www.ozy.com/around-the-world/the-rise-of-digital-tipping-from-music-to-your-own-paycheck/93993/>

reward is voluntary – users’ access to content is not contingent on the monetary reward. Hereafter, we refer to this innovative incentivizing method as the “peer-based monetary incentive”.

Despite the growing business implementation, the impact of the peer-base monetary incentive remains unclear. Previous works have shown that the impact of monetary incentives can be two-fold. On the one hand, the monetary incentive has long been applied and found effective to motivate preferable behavior through the profit effect, such as encouraging healthy activities and student school attendance (Fryer 2011, Volpp et al. 2009). On the other hand, the monetary incentive has proved ineffective in promoting prosocial behaviors due to the crowd-out effect by deteriorating the intrinsic motivation or hurting public image. Producing user-generated content, due to the nature of voluntary creation to share knowledge and experience, is a type of prosocial behavior. Richard Titmuss (1970) argued that providing the monetary incentive can lead to a decrease in quality blood donors due to the crowd out effect. Ariely et al. (2009) found that the monetary incentive would dilute the signal of prosocial acts and decrease the contributor’s image value. As a side effect, a small amount of monetary incentive is found to have a negative impact on prosocial behavior as compared to no money at all.

It is worth noting, however, that prior literature investigating the influence on the monetary incentive usually focuses on the incentive provided by the “governor” such as the platform, the seller, or the government. The business practice applied by UGC platforms described above, however, differs from the conventional understanding and implementation of monetary incentive by having peers to voluntarily provide the monetary incentive. Therefore, receiving a reward can be a signal that the content generator is capable and willing to create high-quality content, building a positive image of the content generator.

Motivated by the unique characteristics and the growing implementations of the peer-based monetary incentive, as well as the conflicting findings of the prior studies, we would like to understand how content generators' participation would be affected by the incentive and the underlying mechanism behind it. We use a unique setting of Chinese UGC social sharing platform to analyze how monetary incentive influences content-generators' behavior. Content generators (hereafter "writers") can post long articles, a type of content that is informative and requires significant effort to generate, on the platform. To encourage the production of high-quality articles, the platform launched a "tipping" feature in December 2014, enabling content consumers (hereafter "readers") to voluntarily provide monetary rewards to writers through money transactions.

Based on the characteristics of the "tipping policy" that content production does not guarantee monetary revenue, we categorize the impact of the policy into two stages: an implementation stage, and a realization stage. When the policy is implemented, a writer, though aware of the tipping policy, has not received any tips from the readers yet. If writers adjust their content generation behavior upon policy implementation, their decisions depend not only on the monetary value they receive, but also the (prior) belief on how likely and how much money they consider themselves to receive. In the second stage, the policy is realized, and the writer has at least received the first tip from the readers. Since then, the impact of monetary reward a writer collects starts to influence the writing decision.

Using the writer's decision of writing as the measure for participation, we first investigate the impact of the policy through regression discontinuity design and an integration of propensity score matching and difference-in-differences analysis. We find that the effect varies at different stages of the policy. When the policy is first implemented, it has a positive impact on the writing

frequency. However, the frequency decreases when writers receive their first tips, but increases later as the writer receives more tips over time.

The result is intriguing and cannot be well justified by the prior theory of monetary incentives. The argument that promotes the profit effect of monetary incentive fails to answer why receiving the first tip hurts participation, and the theory that argues the monetary incentive can demotivate the prosocial behavior can hardly explain the long-term positive impact of the monetary incentive. The result, however, does indicate that a writer's decision is influenced by both the (prior) belief and the realized performance of their articles, indicating that accommodating both the impact of prior belief and the realized performance is necessary for a more comprehensive analysis.

Following this idea, we build a structural model where the writer makes the decision based on the expected payoff, which is influenced by both the prior belief and realized payoff through a Bayesian learning process. Notably, the writer would learn both the monetary value and the social capital value. We find that the impact of the monetary incentive is positive and concave. Besides, the writers tend to overestimate their ability to monetize their content through the tipping policy. The results indicate that the peer-based monetary incentive still influences writers positively, and the temporal negative impact on the monetary incentive is due to the over-estimation of the ability to monetize their content.

We further analyze how the policy would influence the article's quality using the reader's feedback as the measures, and find that both the number of likes and the number of reads increase after the peer-based monetary reward is applied. We also consider the latent heterogeneity in the writer's interest and identify three groups of writers – a star group, a casual group, and a novice group. The star group is reactive to the social incentives only, while the novice group is more

reactive to the monetary incentive. Although the causal group is influenced by the social capital value, the impact is a lot lower than other groups.

The rest of this chapter is organized as follows. Section 4.1 describes the research context and data. In Section 4.2, we construct an empirical model to analyze the impact of the tipping policy on content generation behavior. In Section 4.3, we construct a structural model to investigate the mechanism that leads to the result of the reduced-form analysis. In Section 4.4, we summarize the main findings and discuss contributions, business implications, and potential future extensions of this work.

4.1 RESEARCH CONTEXT AND DATA

Our study is based on a unique setting in a Chinese UGC social sharing platform. The platform serves the role as a combination of Twitter and Facebook, where the content generators can post both microblogs and long articles. Unlike microblogs, where writers can share their thoughts within a limited number of words, the long article poses no upper constraint on the length of the content. Instead, it requires a title, a subtitle, and usually more content to be published. Therefore, compared to microblogs, long articles are often expected to be more informative and takes more considerable effort to produce.

4.1.1 *The Peer-Based Monetary Incentive*

To encourage the writers' participation in producing the informative content, the platform launched a peer-based monetary incentivizing policy at the end of December 2014. The incentive is valid specific to long articles. In particular, it allows readers to voluntarily provide a monetary reward to the writer through direct money transactions. The reward is voluntary to readers because they can decide whether to give a reward *after* reading the full article. In other words, the policy

offers readers a new channel to express their appreciation to the article, without limiting the access to any portion of the content. An analogous example is that Uber riders can voluntarily decide whether to give a tip to the driver after finishing the ride. Based on the voluntary nature of the monetary reward, we hereafter refer to the policy as “the tipping policy”, and the monetary reward as “tips”.

Figure 4.1 (A) and Figure 4.1 (B) provide the readers’ view of after the launch of the policy. Upon reading an article, the readers will find a “tip button”, followed by a list of other readers who have tipped the article before (Figure 4.1(A)). If the reader decides to offer a tip, he clicks the tip button and determines how much to tip, as shown in Figure 4.1 (B). The default tipping value is set by the platform at 9.9 RMB (approximately \$1.5) and is known to all users. Although readers can use the default value as a benchmark when deciding how much to tip, they can offer any tipping value from 0.01 to 10,000 RMB (i.e., the maximum amount to tip is around \$1,500).

From the writers’ perspective, the setup cost to effectively engage in the tipping policy and receive money through readers’ tips is negligible. First, the tipping feature is automatically activated to all users on the platform after the launch of the policy. Second, writers do not need to connect their bank account to the platform to receive money: the money will be stored in the writer’s virtual account on the platform, and connecting a bank account is only required when the writer would like to withdraw the money. Based on the above arguments, we assume that the writers’ behavior, such as writing frequency, will be influenced very soon after the policy implementation. A writer can check his revenue through the interface shown in Figure 4.1 (C). The platform also shows the writer’s monthly income from tips. Notably, the amount of each tip is visible to the writers only. Besides, despite the possibility of receiving a tip, the policy does not guarantee a tip to be collected, nor does it ensure the tipped amount meets the writers’ expectations.



Figure 4.1 Monetary Reward on Long Articles

Given the voluntary nature of the tipping policy, as well as the fact that writers may start receiving money long after the policy implementation, we separate the effect of the policy into two sequential stages. In the first stage, the policy is *implemented*, where writers are aware of the policy but have not received any money yet. In the second stage, the policy is *realized*, where writers have received their first tip and may have more tips over time. Figure 4.2 visualizes how the two effects can potentially influence a writer's behavior sequentially. A writer's behavior change from Period A to Period B represents the effect of the policy implementation, and the boundary of Period B to Period C indicates the starting point of the monetary realization, as a writer can receive multiple monetary incentives over time.

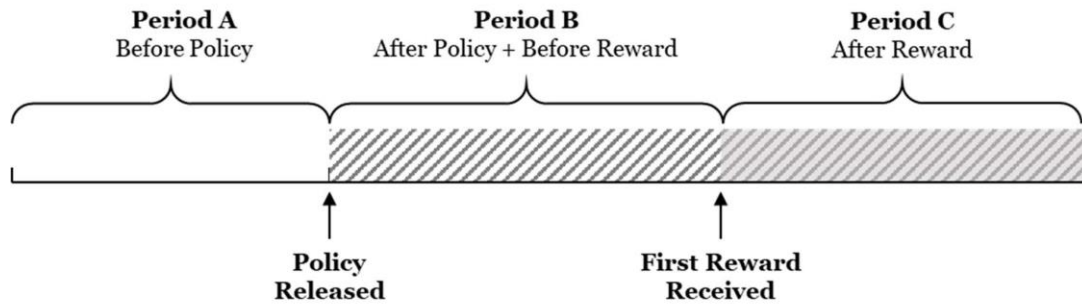


Figure 4.2 Sequential Effect of the Tipping Policy

4.1.2 Data

To study the effect of the implementation and the realization of the tipping policy, we collected the transaction data of the year 2015 from the platform. We randomly sampled 5,000 writers from all the writers who have received at least one tip in 2015. For each of the sampled writers, we collected his article writing history, including the time each article was posted, the article’s content.²⁰ We then collect the readers’ feedback on those articles, such as the number of likes, comments, reposts, whether the article received a tip or not, and the amount of each tip. We also collected the user features of these writers, including gender, tenure on the platform, number of followers, whether the user is verified to be professional in a specific area, and whether he is a VIP user or not.

For later analysis, we focus on a time period from June 2014 to December 2015. we focus on the writers who have written at least one article before the tipping policy implementation to avoid the influence of the impulse-driven writers. We exclude writers whose writing record is incomplete (e.g., those with previous articles deleted) to keep the measurements consistent. We also exclude writers whose tipping revenue shows abnormal patterns, as these patterns usually indicate

²⁰ The article history could date back to the period before the year 2015 if a writer started content generation before the policy implementation.

transaction manipulation. Specifically, we consider two cases: (1) receiving large amounts of tip (over 10,000 RMB) from only one reader in a specific article,²¹ and (2) receiving high tipping revenue from only one reader in the majority of his articles. We end up with 1,994 valid writers who have in total posted 45,236 articles during the period of interest. Table 4.1 provides the summary statistics of the key variables.

Table 4.1 Summary Statistics

Variable		Mean	Med.	S.D.	Min	Max
<i>Measure of Content Generation</i>						
Write _{it}	A binary variable indicating if writer i posted an article in period t .	0.35	0	0.48	0	1
Article _{it}	The number of articles written by writer i in period t .	1.18	0	3.58	0	115
<i>Measures of Readers' Feedback</i>						
Like _{it}	The number of likes received from articles written by user i in period t .	54.95	0	1287.56	0	131306
Cmt _{it}	The number of comments received from articles written by user i in period t .	46.15	0	1350.58	0	234669
Tip _{it}	The tip amount received by user i in period t .	6.294	0	380.75	0	115529
FirstTip _i	The value that writer i receives in the first week that he collected tip	82.15	2.00	889.25	0.01	25000
<i>User-level Features</i>						
Gender _i	A binary indicator of writer i 's gender. =1 if writer is male. =0 if writer is female.	0.52	1	0.50	0	1
Verify _i	A binary indicator of writer i 's verification status. =1 if verified. =0 if not verified.	0.29	0	0.45	0	1
PastArticle _i	The number of articles that writer i has written before policy implementation.	8.37	3	14.49	1	184
Follower _i	The number of users that follows writer i .	122561.80	1053	1442521	1	50524750
Follow _i	The number of users that writer i follows.	544.63	327	766.28	0	18821

Note: Time-varying features are aggregated to weekly level.

For variables with long-tail patterns, (i.e., Like, Cmt, Tip, FirstTip, Follower, Follow), we apply the logarithm transfer in the analysis.

²¹ Note that the upper limit for each transaction is 10,000 RMB. This scenario indicates that one reader has tipped multiple times (with a large amount) to a writer on one specific article.

Notably, the median of the first week's tip value is only 2 RMB, which is a lot smaller than the default value offered by the platform at 9.9 RMB, indicating that the majority of the writers are unlikely to earn the revenue they expected through the policy.

4.1.3 *Model Free Evidence*

In this subsection, we conduct a preliminary analysis to examine how the tipping policy would influence the writer's participation. In particular, we consider two time points: (1) when the policy is first implemented, and (2) when a writer receives the first tip.²²

We conduct a t-test to obtain a general idea of the effect of policy implementation and realization. We use two measures to proxy the writer's participation behavior: a binary indicator of whether to write an article or not, and the number of articles a writer posts within a week. For the policy implementation stage, we compare the content generation behavior before policy implementation (i.e., Period A) and that after the policy implementation, but before the writer receives his first tip (i.e., Period B). For the policy realization stage, we compare the participation in Period B and that after the writer receives the first tip (i.e., Period C).

Table 4.2 shows the result of the test. We find that the effect of the two stages in the policy differs: the policy implementation step has a positive effect on writing frequency, while the policy realization step has a negative impact on writing frequency.

The different impact shown in Table 4.2 is intriguing. It not only shows that the impact of the policy varies over time but also indicates that no money can be better than receiving money. Specifically, when policy is implemented (or announced), writers' participation increases even when they have not received any money yet. When they received their first tip, however, their

²² In the current section, we do not consider the impact of multiple tips in the policy realization stage for simplification.

participation decreases. The result motivates us to build empirical models to better investigate the effect of the policy.

Table 4.2 Effect of Policy on Content Generation

Variable	Effect of Policy Implementation				Effect of Policy Realization			
	Mean		<i>t</i> -test		Mean		<i>t</i> -test	
	Untreated Period A	Treated Period B	<i>t</i> value	Effect	Untreated Period B	Treated Period C	<i>t</i> value	Effect
<i>Quantity Measures</i>								
<i>Write</i>	0.141	0.154	5.37	+	0.154	0.128	-7.05	-
<i>Article</i>	0.279	0.304	3.22	+	0.304	0.246	-8.34	-

4.2 REDUCED FORM MODEL AND RESULTS

In this section, I construct two models to analyze the impact of the policy implementation stage and the policy realization stage, respectively. While the two phases are both attached to the same tipping policy, their underlying mechanism differs. Moreover, policy implementation can be considered as an exogenous shock, while policy realization cannot. Therefore, I apply different identification strategies to investigate the impact on the two stages.

4.2.1 *The Impact of Policy Implementation*

Policy implementation can be considered exogenous as it is based on the decision of the platform and is not influenced by either the readers or the writers. Furthermore, among all the popular user-generated content platforms, this platform is the first one to apply the tipping policy. Thus, writers are less likely to anticipate or adjust their behavior before the implementation of the policy from the competitors' similar business practices. We also eliminated the writers who have never written an article before the policy implementation stage to prevent the potential bias from the policy-impulse writers.

I make use of the exogenous nature of policy implementation and apply a regression-discontinuity (RD) design to investigate the effect, as once the policy is implemented, all users on the platform are influenced (Angrist and Pischke 2008). Specifically, let the probability that writer i posts an article in time period t be:

$$P(\text{Write}_{it}=1)=1/(1+\exp(-ps_{it}))$$

where ps_{it} represents the propensity that writer i will write an article in period t .²³ I apply a sharp RD construction and control for time-varying features.²⁴ Therefore, for each individual writer i , the propensity of writing can be expressed as:

$$ps_{it} = \beta_1 \text{Write}_{it-1} + \beta_2 \text{Like}_{it-1} + \beta_3 P_t + \beta_4 T$$

where Write_{it-1} and Like_{it-1} represents the writing decision in the previous period, and the logarithm transfer of the number of likes received from the previous period, respectively. T is the running time variable, and α_i is the individual fixed effect. P_t is a binary indicator showing whether time period t is after policy implementation. β_3 is the variable of interest, which indicates the impact of policy implementation on the writer's likelihood of content generation. When applying the RD design, a shorter time window is preferable, indicating that the impact of the policy is immediately reflected in the writers' behavior change (Lee and Lemieux, 2011). Therefore, I consider an eight-week (i.e., two-month) period before and after the policy implementation for the analysis. Notably, writers who receive their first monetary reward before the two-month period are excluded from the sample.

²³ For the subsequent parts of this section, I discuss different model specifications for the writing propensity.

²⁴ There is no need to include individual-level time-invariant features since the analysis is conducted for each individual. See, for instance, Anderson (2014) and Busse et al. (2006), for implementation details. I did not include comment count because it highly correlates with the count number.

Table 4.3 Column (1) shows that policy implementation has a significant positive impact on the production of articles. The result indicates that the writers would adjust their content generation behavior without actually receiving the monetary reward. Instead, a message (or signal) showing the potential to collect monetary reward is sufficient to (at least temporarily) encourage the content generation behavior.

Table 4.3 The Impact of Policy Implementation

Variables	(1) RD - Baseline	(2) RD - 7 Wks	(3) RD - 6 Wks	(4) RD - Quadratic
P_t	0.256**	0.256**	0.251*	0.258**
(Policy Implementation)	(0.119)	(0.129)	(0.142)	(0.119)
$Write_{t-1}$	0.224***	0.161*	0.074	0.223**
	(0.087)	(0.092)	(0.099)	(0.087)
$Like_{t-1}$	0.040	0.055	0.071	0.040
	(0.042)	(0.044)	(0.048)	(0.042)
Week	-0.048***	-0.049***	-0.048***	0.020
	(0.012)	(0.014)	(0.018)	(0.134)
Week ²				-0.001
				(0.001)
Observations	10,176	8,554	6,840	10,176

*Standard error in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

We also consider two standard robustness checks to examine the validity of the result: considering different time bandwidth and applying the polynomial approach. The first method examines the impact of the policy at different time windows, especially when the bandwidth is shorter. Therefore, we consider a seven-week and a six-week period before and after the policy implementation. As shown in Column (2) and Column (3) in Table 4.3, the results are qualitatively consistent through different bandwidth, although when the bandwidth is shorter, the significant level decreases (partially due to the limitation of the sample size). The second method captures the potential influence of higher polynomials of the running variable. However, both AIC and BIC criteria suggest that the model without polynomial provides the best fit, and including more polynomial factors hurt the performance in our setting. Therefore, for purely reference purpose,

only the model that includes the quadratic of the running time variable (i.e., the “second best” model) is reported. As shown in Table 4.3, column (4), the result is consistent with that in the original RD specification.

4.2.2 *The Impact of Policy Realization*

The policy realization stage can be further separated into two effects: a short-term effect, where only the impact of the first tip is considered, and a long-term effect, where the impact of all the monetary rewards are accounted.

4.2.2.1 Short-Term Effect of the Monetary Incentive

The short-term effect of policy realization captures the transient stage from Period B to Period C. To investigate its impact, we combine the difference-in-differences (DiD) and the propensity score matching method.

Specifically, we first partition the panel into three parts: April to May, June to July, and August to December. We assign writers who have received their first tip between April and May to the treatment group, and those who have not received their first tip until August to the control group. We focus on a period from April to July, where the ones in the treatment group are treated after receiving their first tip, while the ones in the control group have not been treated throughout the period of interest.²⁵ The model can be specified as:

$$ps_{it} = \beta_1 Treat_i \cdot Post_{it} + \beta_2 Post_{it} + \beta_3 Treat_i + \beta_4 Write_{it-1} + \beta_5 Like_{it-1} + \alpha_i + \tau_t$$

where $Post_{it}$ represents whether writer i has received the first tip at time period t or not. α_i and τ_t represents the individual and time fixed effect, respectively. Let $F_{it} = Treat_i \cdot Post_{it}$ which

²⁵ The panel starts from April to guarantee a sufficient sample in the treatment group (i.e., writers who receive the first tip). It ends in August to guarantee sufficient sample in the control group (i.e., writers who have never received the tip).

equals one if a treated writer has received the first monetary incentive in time period t and equals 0 otherwise. β_1 is the parameter of interest that indicates the impact of the first monetary incentive, which can also be considered the short-term effect of the tipping policy.

It is worth emphasizing that writers who receive tips early (i.e., treated ones) might systematically differ from those who receive the first tip late (i.e., control ones). Therefore, we use the propensity-score matching (Rosenbaum and Rubin, 1985) approach to take care of the potential selection issue brought by the observable individual features.²⁶ In particular, we match based on the writer portfolio (e.g., Gender, Verify, Follower, Follow) and writer’s past performance (e.g., PastArticle, FirstTip). After the match, we have 163 treated writers and 163 controlled counterparts.

Column (2) in Table 4.4 presents the estimation result of the DiD construction using the matched sample. We present the result of policy implementation in Table 4.4, column (1) for reference. The result shows that, consistent with the preliminary finding, receiving the first tip negatively influences the writers’ participation, and the impact of the short-run policy realization stage contradicts that of the policy implementation stage.

Table 4.4 The Impact of the Tipping Policy on Different Stages

	(1) Policy Implementation	(2) Policy Realization - Short-run	(3) Policy Realization - Long-run
P_t (Policy Implementation)	0.256** (0.119)		
F_{it} (First Tip Received)		-0.310*** (0.026)	
Rwd_{t-1}			0.061*** (0.011)
$Write_{t-1}$	0.224*** (0.087)	1.023*** (0.025)	1.011*** (0.025)

²⁶ The propensity-score (i.e., ps_{it}^{Tip}) represents the propensity to receive the first tip. It differs from the propensity score in Eq. (1) and all other model specifications, where ps_{it} represents the propensity to write an article.

Like _{t-1}	0.040 (0.042)	0.114*** (0.009)	0.096*** (0.009)
Week	-0.048*** (0.012)		
Time FE	-	Y	Y
Writer FE	-	Y	Y

*Standard error in brackets. * p<0.1, ** p<0.05, *** p<0.01*

4.2.2.2 Long-Term Effect of the Monetary Incentive

Upon receiving the first monetary reward, a writer, over time, can receive multiple tips, whose impact may differ from the short-term effect of the first tip. Moreover, the long-term effect is often the interest of the platform owner. Therefore, it is also necessary to investigate the impact of the sequential monetary reward.

To take care of the potential influence of the historical monetary rewards on the content generation behavior, we model writer i 's propensity to write article in time period t as:

$$ps_{it} = \alpha + \beta_1 Rwd_{it-1} + \beta_2 Write_{it-1} + \beta_3 Like_{it-1} + \alpha_i + \tau_t \quad (2.1)$$

where Rwd_{it-1} represents the value of monetary incentive, which is the logarithm transfer of the total amount of tips received by writer i in week t . The estimation result is shown in Table 4.4 Column (3). We find that differ from the short-term negative impact, the long-term effect of the monetary value is positive.²⁷ The result shows that in the long run, the peer-based monetary incentive is likely to benefit the content production.

4.3 THE STRUCTURAL MODEL AND RESULT

The reduced-form analyses show that the impact of the tipping policy is, in general, positive. However, the impact is inconsistent at different stages of the policy. Besides, prior literature is unlikely to provide an explanation for these results. Specifically, the literature that suggests

²⁷ The result is qualitatively consistent when other measures or specifications, such as the frequency of tips or including the quadratic terms, are used to represent to impact of the monetary incentive.

monetary incentive is effective in promoting content generation behavior by directly improving the writer's revenue cannot explain the short-term negative impact on content generation upon receiving the tip. Meanwhile, the theory that emphasizes the crowd-out effect of the monetary incentive on prosocial behavior, such as content generation, does not address the long-term positive impact of tipping value and frequency.

The results, however, does deliver two pieces of information. First, the long-term effect indicates that a writer's behavior is influenced by the past performance of her article. Second, the influence of the policy implementation stage indicates that a writer's decision is also influenced by the perceived payoff from the tipping policy, especially the prior belief, as no monetary incentive has been realized yet.

The result that a writer's decision is influenced by both the prior belief and the past performance motivated us to apply a structural model and construct the perceived payoff to describe the writer's decision-making process, where the perceived payoff is initially the prior belief, and keeps being updated as the writer collects more information through the writing performance. Using a structural model not only helps to accommodate the impact at different stages but also helps to depict the dynamics of the content generation decision.

4.3.1 *The Utility Function*

We start by specifying the writer's utility function to model the decision of content production. We consider two factors – the writer's payoff and the writer's cost of writing as the factors that influence the writing decision. Specifically, the utility that writer i produces an article in period t can be specified as:

$$U_{it} = c_i + \beta_1 S_{Eit} + \beta_2 S_{Eit}^2 + (\beta_3 R_{Eit} + \beta_4 R_{Eit}^2) A_t + e_{it}$$

where c_i is the writing cost of writer i . S_{Eit} is the social capital value that writer i experienced in period t . It measures a writer's payoff through social capital, such as benefiting the readers, and captures the main payoff of most conventional user-generated content setting where no other incentive is available. R_{Eit} represents the monetary value that writer i experienced in period t . It measures a writer's payoff through receiving tips from the readers. The quadratic term of S_{Eit} and R_{Eit} are included to capture the potential curvature with respect to the two features. A_t is a binary variable indicating whether time period t is after the policy implementation, and equals 1 if the policy has already implemented. Therefore, before the policy implementation, only the social capital value and the writing cost would influence a writer's decision.

Before writing an article, a writer is not sure about how many likes and how much tip she would collect through the article. Therefore, she is uncertain about her social capital value and the monetary value on the platform. She will, however, form up an expectation on the two factors based on the information she collected, such as the performance of the articles she has written previously, and make writing decisions accordingly.

Let $I(i, t)$ be the information set that writer i obtains up to time period t . Then, $E[U | I(i, t)]$ is the expected utility writer i receives at time period t , conditional on her information up to period t . Thus, the expected utility can be reformulated as:

$$E[U | I(i, t)] = \tilde{U}_{it} + e_{it} = c_i + \beta_1 S_{it}^e + \beta_2 S_{it}^{e2} + (\beta_3 R_{it}^e + \beta_4 R_{it}^{e2}) A_t + e_{it}$$

where $S_{it}^e = E[S_{it} | I(i, t)]$ is the expected social value based on writer i 's information set, and $R_{it}^e = E[R_{it} | I(i, t)]$ is the expected monetary value conditional on i 's information. c_i is known to the writer and has no uncertainty.

4.3.2 *The Bayesian Learning Process*

In this section, we describe how we construct the expected values that influence the writer's expected utility. Consistent with the findings in Section 4.2, we consider that a writer forms up the expected payoffs (i.e., social capital value and monetary value) based on two factors: the prior belief and the past payoff collected. Specifically, we consider that a writer updates her belief through a Bayesian learning process.

The overview of this procedure is described in Figure 4.3. When a writer has not written any articles yet, she would first form up a prior belief on the social capital value and the monetary value (upon the implementation of the tipping policy), based on which she decides whether to write an article or not. If she writes an article, she will start to collect readers' feedback from two sources: the number of likes she receives, and the tipping amount she collects. She would use the information as a signal to update her belief in the social value and monetary value correspondingly. If she does not write, no information would be collected, and her belief does not change. It is worth emphasizing that the learning behavior of the social capital is naturally embedded on the platform, as the "like" feature is always available for long articles. The learning of monetary value, however, starts when the tipping policy is implemented, before which the monetary value is zero, as no such feature is available yet.

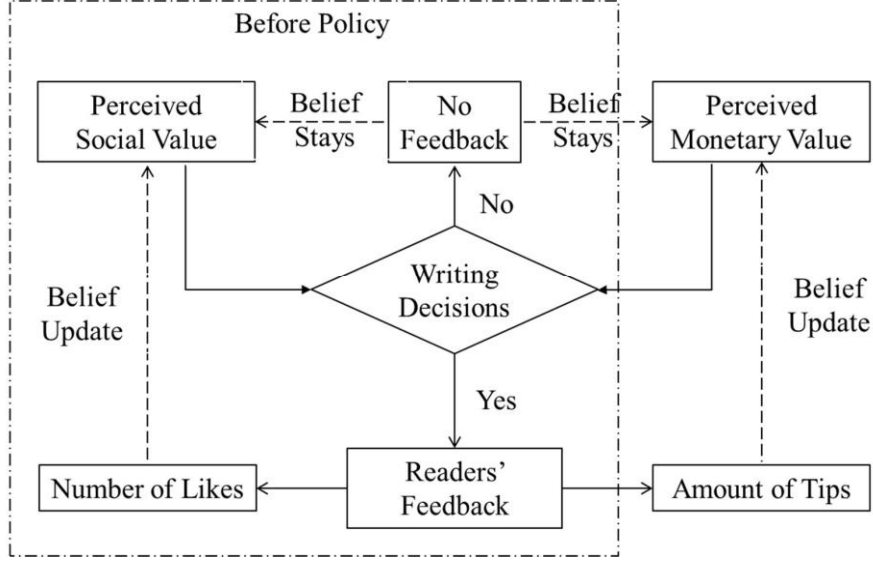


Figure 4.3 The Writers' Belief Updating Process

The above procedure can be formalized below. Let S_i be writer i 's true social value (i.e., the value to benefit other readers), and R_i be writer i 's true monetary value (i.e., writer's ability to monetize her content through the tipping policy). If she decides to write an article, she will receive several likes (denote by S_{it}) and tips (denote by R_{it}) from her readers.²⁸ We assume that the two features, S_{it} and R_{it} , are the signal for social value and monetary value, correspondingly, indicating that they carry partial information of the underlying true value of S_i and R_i . Therefore, the relationship can be expressed as: $S_{it} = S_i + \mu_{it}$, where $\mu_{it} \sim N(0, \sigma_\mu^2)$, and $R_{it} = R_i + \nu_{it}$, where $\nu_{it} \sim N(0, \sigma_\nu^2)$. Following Bayes Rule, the writer will update her belief shown below:

$$R_{it}^e = R_{it-1}^e + (R_{it} - R_{it-1}^e) \frac{\sigma_{R_{it-1}}^2}{\sigma_{R_{it-1}}^2 + \sigma_\nu^2} \quad \text{and} \quad S_{it}^e = S_{it-1}^e + (S_{it} - S_{it-1}^e) \frac{\sigma_{S_{it-1}}^2}{\sigma_{S_{it-1}}^2 + \sigma_\mu^2}$$

²⁸ Note that S_{it} and R_{it} depend on the decision of the readers. The observed feature (S_{it}, R_{it}) is the equilibrium outcome of the general audience. Writers, instead of forming expectations for each reader, forms expectation of these equilibrium outcomes directly.

where $\sigma_{R_{it}}^2 = \left(\frac{1}{\sigma_{R_{it-1}}^2} + \frac{1}{\sigma_v^2} \right)^{-1}$, and $\sigma_{S_{it}}^2 = \left(\frac{1}{\sigma_{S_{it-1}}^2} + \frac{1}{\sigma_\mu^2} \right)^{-1}$.

When the author has not written any articles, her expected social capital value is the same as the prior belief. Similarly, when the tipping policy has been implemented, but the author has written any articles, the expected monetary value is the same as the prior belief. Therefore, the initial states can be expressed as: $S_{it_{S_0}}^e = S_0$, and $R_{it_{R_0}}^e = R_0$, where $t_{S_0} = 0$ and $t_{R_0} = 52$.

The writer makes her decision based on her expected payoff for writing. We normalize the utility for outside option (i.e., not writing an article) to zero, and the probability of writing is:

$$P(W_{it} = 1) = \frac{1}{1 + \exp(-\tilde{U}_{it})}$$

Following Erdem and Keane (1996), we use maximum likelihood method for parameter estimation. Table 4.5 presents the result of the structural model.

Table 4.5 The Estimation Result of the Structural Model

Variables	Estimate	S.D.
<i>Learning Stage</i>		
Monetary Value – Initial Belief	2.709***	0.002
Social Capital Value – Initial Belief	5.744***	0.037
Monetary Value – S.E.	1.552***	0.014
Social Capital Value – S.E.	1.913***	0.014
<i>Decision Stage</i>		
Writing cost	-1.216***	0.025
Monetary Value – Linear	0.133***	0.014
Monetary Value – Quadratic	-0.019***	0.002
Social Capital Value – Linear	-0.036***	0.003
Social Capital Value – Quadratic	0.001***	0.000

The results show that after considering the learning behavior, the influence of the peer-based monetary award on the writer's content production is positive and concave. Besides, the initial belief of the monetary value is greater than the mean of the monetary reward, indicating that writers tend to overestimate their ability to monetize their content. It also explains the seemingly

conflicting result from the reduced form analysis – the short-term negative effect is not because of the deterioration of the social image, but because of the biased prior, which results in an over-production of the articles. As a writer receives more tips and her belief converges to the true monetary value, her participation decreases, adjusting the over-estimated prior. The positive impact of the peer-based monetary incentive indicates that the platform’s motivation method is effective, and a proper design of motivation tool (e.g., combining monetary incentives with readers’ appreciation) can reduce (if not resolve) the crowd-out effect.

4.4 EXTENSIONS: QUALITY AND HETEROGENEITY

4.4.1 *The Impact on Content Consumers’ Feedback*

So far, we have shown the positive impact of peer-based monetary incentive on content production. However, it is worth emphasizing that not only the content quantity but also the content quality is of the particular interest of the UGC platforms. Low-quality content not only fails to deliver knowledge and information but also hurts the image of the platform. Therefore, in this subsection, we investigate how the peer-based monetary incentive would influence the content quality.

Two measures are considered to represent the quality of content – number of likes and number of reads. The number of likes evaluates the writer’s value from the reader’s perspective. Assuming that readers are more likely to appreciate content of higher quality, an article with more likes can be regarded as higher quality contents. The number of reads also evaluates the writer’s value from the platform’s perspective – writers whose articles can bring more traffic not only shows that the content is attractive but can also bring greater advertisement revenue to the platform.

The impact of the tipping policy on the quality measures of the content can be written as:

$$Quality_{it} = \beta_0 + \beta_1 Write_{t-1} + \beta_2 Like_{t-1} + \beta_3 Rwd_{t-1} + \alpha_i + \tau_t + \varepsilon_{it} \quad (2.2)$$

where $Quality_{it}$ represents the quality measure which takes $Like_{it}$ and $Read_{it}$, correspondingly.

It is worth noting that these measures are available only when a writer decides to write an article. Otherwise, all these measures would be missing. To account for the issue of missing data, we apply the standard Heckman Correction (Heckman 1979), a two-stage model which first describes the choice of writing, then describes the influence on the outcome variables. The second stage is described in Equation (2.2), and the first stage is described in Equation (2.1) in Section 4.2.

Table 4.6 shows the impact of the tipping policy on the content quality. We find that the impact of monetary reward is positive and significant for both measures, although the influence on the number of likes is relatively marginal. In the meantime, the impact of monetary incentives is smaller than that of the social incentive.

Table 4.6 The Impact on the Readers' Feedback of Content

	Number of Likes	Number of Reads
Like _{t-1}	0.117*** (0.015)	0.127*** (0.025)
Rwd _{t-1}	0.044* (0.023)	0.116*** (0.037)
Constant	0.257 (0.284)	2.195*** (0.407)
Observations	14,863	14,863

*Standard error in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

The result indicates that the peer-based monetary incentive can not only promote content production but also lead to a better consumers' reaction towards the content. Therefore, the incentive addresses the concern where the monetary incentive might deteriorate the writer's intrinsic motivation and sacrifice content quality for quantity. The issue is resolved by having the peers to voluntarily provide the monetary incentive, where both the contingency on content quality and the role of being appreciated by peers promote more content of higher quality.

4.4.2 *The Latent Heterogeneity of Content Generators*

Another concern is the heterogeneity in the users' intrinsic motivation to engage in the platform. The intrinsic motivation to participate in a social sharing platform can be significantly different. Some writers might consider the platform as a private blog to write down their experiences, while others may seek to gain exposure and even monetize their popularity. Consequently, their preferences and reactions towards the different incentives can be different, and it is important to consider the potential heterogeneity.

The intrinsic motivation is unobservable, and the heterogeneity among users cannot be directly obtained. Therefore, we apply the Finite Mixture Model to capture the latent heterogeneity in the writers' preferences based on the writer's past performance and content generation behavior. Specifically, we consider S groups of writers, each of which has its own preference towards the monetary and social incentives, resulting in S sets of parameters noted by $\vec{\beta} = \beta^1, \beta^2, \dots, \beta^s$, where $\beta^s, g = 1, 2, \dots, S$ represents the preferences of writers in group g . Further let $\pi_g, g = 1, 2, \dots, S$ be the probability that a writer belongs to group g . Therefore, the conditional probability that writer i in group g follows the observed sequence of content production is:

$$L_{i|g} = \prod_{t=1}^T \left(\frac{\exp(\beta^s \mathbf{x}_{it})}{1 + \exp(\beta^s \mathbf{x}_{it})} \right)^{w_{it}} \left(\frac{1}{1 + \exp(\beta^s \mathbf{x}_{it})} \right)^{1-w_{it}}$$

where \mathbf{x}_{it} represents the characteristics that influence the writer's decision.

We are unable to observe which group each writer belongs to. However, we are able to obtain the likelihood of writer i 's sequential behavior for each possible group, based on which we infer the group the writer belongs to. Specifically, after considering all potential groups, the writer's likelihood can be written as:

$$L = \prod_{i=1}^N \sum_{g=1}^S L_{i|g} \cdot \gamma_{gi}$$

where γ_{gi} is the probability that writer i belongs to group g .

Maximizing the likelihood function is equivalent to maximizing the log likelihood below, which is less computationally heavy.

$$\log L = \sum_{i=1}^N \sum_{g=1}^S L_{i|g} \cdot \gamma_{gi}$$

We conduct the estimation through E-M algorithm and determine the optimal number of groups (i.e., S) through AIC and BIC criteria. Our results show that three latent groups are identified, each of which reacts differently in terms of the magnitude of the incentives.

As a non-parametric method, the Finite Mixture Model does not provide which factors influence the writers' group assignment. Therefore, we visualize the features of different groups to better understand the behavior of each group. Figure 4.4 provides several main characteristics (namely, the log of number of followers, the tenure on the platform, and the articles written before the tipping policy) of the different groups of writers. We find that the writers that belong to the right-hand side of each subfigure distinct from other groups by having the least number of followers, the shortest time on the platform, and the smallest contribution before the policy. Therefore, we refer to this group of writers as the “novice group”, as they are not only new to the platform but also has the least popularity and historical contribution. These writers consist of around 20% of the total sample. The writers in the middle of each sub-figure performs the best among all figures – they have written the greatest amount of articles, largest social network, and longest tenure (though not distinguishable from the second place). Therefore, we refer to these writers as the “star group”, which are around 10% of all writers. The writers who are assigned to the left-hand side has the medium performance on all the features – relatively long tenure, medium

network size, and medium past contribution. We refer to them as the “casual group”, which takes around 70% of all the writers.

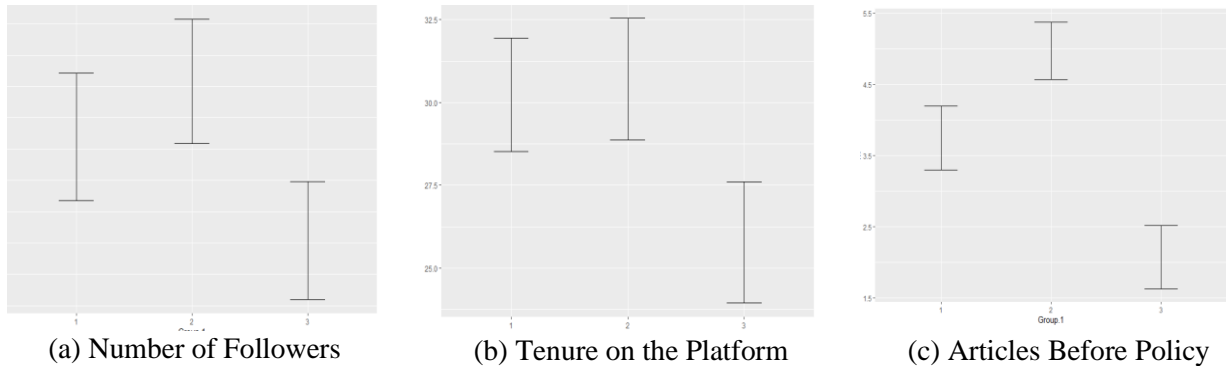


Figure 4.4 The Characteristics of Different Groups of Writers

The preference towards the social and monetary incentives of each group of writers are presented in Table 4.7. We find that the casual writers are not influenced by the monetary incentive but react positively to the social incentive. Notably, the size of the impact of social incentive is relatively small, and the significant level is at the boundary. In general, this group of writers barely react to any of the incentives. Interestingly, the star writers are not responsive to the monetary incentive but react significantly to the social incentive. One of the explanations is that the star writers are able to monetize their content through other more prolific channels, such as advertisement, and the monetary incentive through tipping is not sufficient to promote content production. The novice group are influenced by the monetary incentive most. This could be because they are new to the platform and are more eager to establish their reputation or monetize their content.

Table 4.7 The Heterogeneous Influence on Content Generation

	Casual	Star	Novice
Like _{t-1}	0.090* (0.047)	0.163** (0.055)	0.121* (0.071)
Rwd _{t-1}	0.033 (0.066)	-0.004 (0.083)	0.278*** (0.079)
Write _{t-1}	0.484*** (0.072)	1.219*** (0.075)	1.431*** (0.110)

Constant	-2.490*** (0.158)	-1.919*** (0.220)	-3.386*** (0.176)
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*Standard error in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

4.5 CONCLUSION AND DISCUSSION

Motivated by the growing significance of user-generated content as well as the practitioners' attempt to encourage the content generation process through monetary reward, we intend to understand how a peer-based monetary incentive would influence content-generators' writing behavior. Using data from a social content-sharing platform that applies the peer-based monetary reward to motivate content generation, we first apply panel data analysis and find a different effect of policy implementation and realization in a writer's participation behavior. Specifically, the participation increases when the policy is implemented, and the writers have not received any money yet, while experiences a short-run decrease when writers receive their first tips, followed by a long-run increase in the value of the tipping value.

We then build a structural model that accommodates the writer's potential learning behavior, which considers the influence of both the writer's prior belief and the performance of past-written articles. Our results indicate that after considering a writer's learning behavior, her participation is positively influenced by the monetary value. Besides, writers tend to overestimate their revenue-generation ability, resulting in a temporary negative effect on content generation. A further analysis shows that the articles written after the tipping policy obtains better feedback from the consumers, in terms of the number of likes and the number of reads. We further extend the analysis to accommodate for the users' latent heterogeneity through a finite mixture model and identify three group of users – a casual group, who are not or marginally responsive to either the monetary incentive or the social incentive; a novice group, who are especially reacting to the monetary incentive significantly, and a star group who are responsive to the social incentive only. This work

contributes to two streams of literature: user-generated content and monetary incentive. It extends the literature in user-generated content production by showing the effectiveness of an innovative monetary incentive. Prior research on the user-generated content production either focuses on the value of non-monetary factors or studies the impact of monetary incentive on product reviews. Consequently, the influence of monetary incentive offered by the peers is left uninvestigated. By showing a positive impact on both content production and the content consumers' feedback on the content, we argue that a quality-contingent (through the voluntary nature using tips) monetary incentive helps to alleviate the concern of the quality reduction. It also addresses the dilemma of applying the monetary incentive to motivate prosocial behavior such as content production – when peers are the incentive providers, the monetary incentives integrates the role of extrinsic motivation (through monetary reward) and intrinsic motivation (by expressing the appreciation of the content). Therefore, not only the value, but also the provider of the monetary incentive is essential in influencing the prosocial behavior.

Our work also helps with the platform decisions. Distinct from the prior studies that show the social network, such as number of followers, would influence the effectiveness of the incentive, we argue that based on the diversity of the UGC platform, it is more important to identify the latent preference based on their past behavior and performance. Casual writers may not react to the monetary incentive even though they have established relatively large social network due to the duration on the platform. Identifying the group the writers belong to can help better target the writers that are responsive to the incentive.

Chapter 5. FREEMIUM PRICING IN DIGITAL GAMES WITH VIRTUAL CURRENCY

The digital game industry has been growing tremendously in the past few years. Annual sales of video game content in the United States (including mobile apps, social network gaming, digital add-on content, etc.) have increased from \$17.6 billion in 2011 to \$23.2 billion in 2015 (ESA 2017). One of the most successful revenue models in this booming industry is the freemium model – providers do not charge for gameplay and basic functions of a game, but charge for the premium content of it. Games adopting such strategy, usually known as *free-to-play games*, have dominated the market. By 2014, over 90% of the mobile gaming revenue in App Store comes from free-to-play games (Calinescu 2014). Top grossing iPhone free-to-play games such as Mobile Strike and Pokémon Go each earns over \$300,000 per day (ThinkGaming 2017). One game provider, Supercell Oy, made €2.1 billion (\$2.3 billion) revenue and €848 million (\$924 million) profit in 2015 with only three free-to-play games (PrivCo 2017).

Game providers who produce free-to-play games often rely on two methods to earn profit: (i) monetizing players' playtime, and (ii) selling the premium content of their games. The former method can be realized through in-game advertising. In-game advertising contains different advertisement patterns such as banner ads, interstitial ads, background ads, etc. According to a survey by DeltaDNA (2015), such monetizing tool on average contributes to around 38% of total revenue of free-to-play games. We hereafter refer to the profit generated from players' playtime as the provider's time profit. Meanwhile, game providers also generate direct revenue through selling premium content, a gaming module that helps players to obtain better gaming experience. Premium content can improve players' experience from various aspects, such as providing new gaming episode or boosting gameplay efficiency.

Regarding how to sell the premium content, an increasing number of games adopt a new selling strategy – virtual selling strategy. Taking advantage of the “virtual” nature of digital games, providers set up an in-game currency (such as “coins” or “gems”), which can be gained either through direct purchase using real currency, or through additional playtime. For instance, players can earn virtual currency as a reward after completing gaming levels or solving puzzles. The provider will set the gaming module’s price directly based on virtual currency, and players can make up for the amount to purchase through either method mentioned above. For the ease of presentation, we hereafter refer to the method of using real currency as the currency exchange, while the method of using playtime as the time exchange. Many of the free-to-play games have achieved tremendous success by adopting the virtual selling strategy. Clash of Clans, one of the most successful free-to-play games that use virtual selling strategy, generates around \$2 million of revenue per day from iPhone users in US market in May 2017. Candy Crush Saga, another famous free-to-play mobile game using similar virtual selling strategy, generates daily revenue at around \$1 million during the same period (ThinkGaming 2017).

Despite its growing popularity, limited research has been conducted to analyze the new virtual selling strategy, especially regarding how it leads to market outcomes different from the traditional real selling strategy where players can purchase the premium content using real currency directly only. Our study aims at filling the gap and particularly focuses on the market outcomes caused by one distinguishing feature of the virtual selling strategy – players can purchase the premium content indirectly using their playtime, i.e., the time exchange. Specifically, we ask the following questions: Compared to the real selling strategy, will the virtual selling strategy benefit a game provider or a player since it allows the time exchange? Through which mechanism it may benefit

or hurt a provider or a player? Will the virtual selling strategy, due to its permission of the time exchange, lead to any result that contradicts the traditional beliefs from the real selling strategy?

We start our analysis by characterizing the effect of premium content on players' gaming utility. In reality, premium content may boost players' gaming utility in various ways. In this study, we focus on the aspect where premium content provides players new gaming stages like new gaming episodes. For ease of presentation, we hereafter refer to the premium content as the module. We also narrow down the scope of our study to the type of games which do not exhibit strong network effect, for examples, Angry Birds, Candy Crush Saga and other high-ranking puzzle games like Wordscapes and strategy games like Plants vs. Zombies 2.

Our results show that the virtual selling strategy, by allowing the time exchange, will benefit, or at least not hurt, the provider's profit compared to the real selling strategy. Perhaps interestingly, the reason for such potential profit improvement is *not* that the virtual selling strategy enables the provider to further discriminate against players based on their willingness to pay for the module. On the contrary, the virtual selling strategy produces reverse price discrimination in the market equilibrium – players with higher willingness to pay, when purchasing the module, pay²⁹ *less* for the module compared those with lower willingness to pay. The reason for such reverse discrimination is first that the players with higher willingness to pay are in general the ones with lower time cost of playing the game – they tend to play the game more such that the module provides more additional utility for them compared to those players who have higher time cost and thus play the game less. Then the virtual selling strategy gives those players with low time cost a cheaper option, i.e., the time exchange, to purchase the module compared to the relatively more expensive option, i.e., the currency exchange, which will be adopted by the players with high time

²⁹ Throughout this paper, we use the word “pay” to refers to the action of incurring a net utility reduction in order to acquire the module. The reduction can be caused by either a monetary payment or incurrence of time cost.

cost. Although the players with low time cost pay less, their excessive playtime spent on acquiring the module will generate more profit than how much the provider could earn had they chosen the currency exchange. In other words, the virtual selling strategy, instead of enabling the provider to further discriminate against players based on their willingness to pay, enables the provider to selectively transform players from the provider's direct profit source to her vehicle to draw profit from sponsors, e.g., advertisers. By transforming the players who are most capable of drawing time profit, i.e., the ones with the lowest time cost, virtual selling strategy leverages the heterogeneity of players' time cost and eventually benefits the provider.

Perhaps interestingly, although the virtual selling strategy provides players an additional way, i.e., the time exchange, to purchase the module, it will hurt, or at least not benefit, consumer surplus overall compared to the real selling strategy. It may even lead to a reduction of *every* player's surplus – including those with the lowest time cost – if the provider's time profit from a unit of playtime of a player, hereafter we refer to as the time revenue rate, is sufficiently high. We identify an undocumented effect – the complementary effect – which causes the surplus reduction. Note that anecdotal evidence often refers to players who use playtime to purchase a module as “play-to-buy” players and others who use real currency, either directly (i.e., not using virtual currency as an intermediate) or indirectly (i.e., through the currency exchange), to purchase a module as the “buy-to-play” players. When a provider switches from the real selling strategy to the virtual selling strategy, it will convert a group of players with low time cost from buy-to-play players to play-to-buy players. One interesting property of the emerging play-to-buy players is that each of their profit margin will increase in the module price at a *faster* rate than what it used to be when he was a buy-to-play one in the real selling strategy, if the time revenue rate is above a threshold. Meanwhile, due to their low time cost, the emerging play-to-buy players also have a higher

willingness to pay for the module than the remaining buy-to-play ones. Hence the provider, after switching to the virtual selling strategy, will raise the module's equivalent price – the net amount a player needs to pay to acquire the module. Although some buy-to-play players will churn, the play-to-buy players will stay due to their higher willingness to pay and overcompensate the loss of buy-to-play players based on their higher marginal rate of profit margin to price. We refer to such an overcompensation from the play-to-buy players as the complementary effect. We find that the higher the time revenue rate, the stronger the complementary effect, the more the provider will raise the equivalent price, and eventually, the greater the reduction on every player's surplus. When the time revenue rate is sufficiently high, every player's surplus will be hurt by the virtual selling strategy. When the time revenue rate is moderate, for the play-to-buy players with the lowest time cost, the corresponding rise of the equivalent price may not be able to override the benefit brought by the time exchange itself, i.e., a cheaper way to acquire the module via playtime. Hence it will lead to a local win-win outcome in such a market condition – the provider and the players with the lowest time cost are better off with the virtual selling strategy compared to the real selling strategy.

The virtual selling strategy also produces a perhaps interesting U-shaped relationship between the equilibrium module price and the time revenue rate when the module only provides a small number of new gaming stages. It contradicts the traditional belief that a content provider shall reduce its content price when she can finance the content through in-content ads more efficiently. The reason for the U-shaped relationship is also the complementary effect. Due to the complementary effect, when the time revenue rate increases, the provider will make it faster for players to earn virtual currency via playtime – it will induce more players to become play-to-buy ones, such that the overcompensation becomes stronger and the provider's profit becomes higher. A side effect of the higher earning rate is inflation – players will have more virtual currency in

their pockets when they want to buy the module. Hence, the provider will want to raise the module price to account for the inflation. On the other hand, the provider, like in the traditional real selling strategy, will want to reduce the module price, i.e., subsidizing players, to expand the total market adoption when the time revenue rate increases. For a module which only provides a few gaming stages, the inflation is weaker than the subsidization, such that the module price decreases in the time revenue rate when the rate is low. When the rate is high, the inflation is stronger than the subsidization, such that the module price increases in the time revenue rate.

The rest of this chapter is organized as follows. In the next section, we present the model for the free-to-play games and the virtual selling strategy. In Section 5.2, we derive the optimal strategies for the players and the provider, and then compare the equilibrium outcomes between the virtual selling strategy and the real selling strategy. In Section 5.3, we consider players' heterogeneous gaming skill levels. Finally, we conclude the findings and discuss future work in Section 5.4.

5.1 THE BASE MODEL

Consider a game provider who offers one free-to-play game to a unit mass of players. A player's gaming utility U consists of two parts: gaming leisure L and cost of playing. His cost of playing depends on playtime t and time cost c . Specifically, we define

$$U = L - c \cdot t .$$

Players are heterogeneous in terms of their time cost c . A higher c suggests that the player has more valuable alternative activities for the time spent in the game. We assume c is uniformly distributed between $[\underline{c}, \bar{c}]$. Without loss of generality³⁰, we set $\underline{c} = b$ and $\bar{c} = 1 + b$, where $0 < b < 1$.

A player's gaming leisure L is associated with his gaming stage S . A player's gaming stage indicates how much content of the game the player reaches. Once a player starts the game and reaches more gaming content, his gaming stage increases, and the player generates more gaming leisure from the game during the process. The exact relationship between gaming leisure L and gaming stage S depends on the specific game design. In this study, we examine the games where gaming leisure L increases in gaming stage S at a marginally diminishing rate. Specifically, we define:

$$L = S - \frac{S^2}{2} .$$

Denote the maximum gaming stage by \bar{S} which corresponds to reaching all the gaming content. Without loss of generality, we set $0 < \bar{S} \leq 1$.

A player can reach later gaming stage S with longer playtime t . The exact relationship between gaming stage S and playtime t also depends on the specific game design. For simplicity, we assume that gaming stage S is influenced by playtime t in a linear pattern. Thus, if all the gaming content is offered for free, we have:

$$S = \lambda \cdot t \text{ when } 0 \leq t \leq \bar{S} / \lambda ; \text{ and } S = \bar{S} \text{ when } t > \bar{S} / \lambda ,$$

where $\lambda > 0$. Note that parameter λ indicates a player's gaming skill level. A player with a higher (lower) gaming skill level generally advances through the game faster (slower), such that he is

³⁰ Upper bound \bar{c} can be any value greater than one and lower bound \underline{c} needs to be less than one otherwise no player will play in the first place according to the subsequent setting on gaming leisure L . The specific number of \bar{c} does not affect the main insights of the paper. Hence, we set it to $1 + b$ to have a unit probability density function to simplify the analysis.

associated with a higher (lower) λ . For the base model, we assume that all players have the same gaming skill level. In Section 5.3, we relax this assumption and consider heterogeneous gaming skill levels.

Freemium modeling: Under the freemium model, not all the gaming content is offered free. Specifically, players can only reach gaming stage $S = a$ where $a < \bar{S}$ for free. Access to the later gaming stage $S > a$ will require players to acquire a premium gaming module (hereafter referred to as “module”). For example, in a free-to-play game Candy Crush, players can reach content only up to a “tricky gaming level”. The level is usually difficult enough so that players who do not purchase the module cannot complete it, and thus are unable to get access to content afterward. In other words, without acquiring the module, once a player reaches gaming stage $S = a$, his gaming stage would be stagnated at that point. Hence, we define the relationship between gaming stage S and playtime t in the freemium model:

$$S = \lambda \cdot t \text{ when } 0 \leq t \leq a / \lambda, \text{ and } S = a \text{ when } t > a / \lambda.$$

If the player acquires the module, he unlocks the gaming stage from $S = a$ to $S = a + h$. Parameter h characterizes the module’s *game-continuation value* (hereafter referred to as “continuation value”) – a higher h will allow the player to reach more advanced stage of the game. For ease of presentation, denote the maximum free gaming stage by $S_{NP} = a$ and the maximum game stage with the module by $S_p = a + h$.

Based on the decisions on whether to acquire the module, the players choose their optimal playtime t^* to maximize their gaming utility. Denote the optimal gaming utility of a player without the module by U_{NP} and with the module by U_p . We derive:

$$U_i = \max_t \{L - c \cdot t\} \text{ s.t. } S = \lambda \cdot t \text{ when } 0 \leq t \leq S_i / \lambda; \text{ and } S = S_i \text{ when } t > S_i / \lambda,$$

where $i \in \{P, NP\}$. Eventually, optimal utility difference $U_P - U_{NP}$ represents a player's net willingness to pay towards a module with continuation value h . The next question is whether a player will pay for the module.

Virtual Currency Selling: Suppose a player can acquire the module by paying w amount of virtual currency value. If not explicitly stated otherwise, hereafter we use “ x amount of virtual currency value” to refer to the amount of virtual currency that worth x amount of real currency. In other words, we refer to an amount of virtual currency not by its nominal amount, such as one hundred virtual coins, but by the amount of real currency that has the equivalent value according to the real-to-virtual currency exchange.³¹

Virtual currency can be obtained in two ways: either through playtime or through the real-to-virtual currency exchange. We hereafter refer to the first way to obtain virtual currency as “time exchange” and the second way as “currency exchange”. Regarding the time exchange, recall that a player will go through λ gaming stages per unit time. Suppose for each gaming stage a player goes through, he can earn k amount of virtual currency value. We hereafter refer to k as the rate of earning virtual currency value, or in short, the earning rate. Hence, a player will eventually earn $\lambda \cdot k$ amount of virtual currency value per unit time.

Based on the setup, a player who reaches the maximum free gaming stage $S = a$ and thus may need the module to access later gaming content has already earned $a \cdot k$ amount of virtual currency value from their playtime. To acquire the module, he can (i) spend additional playtime to earn (i.e., the time exchange), or (ii) use real currency to buy (i.e., the currency exchange), or (iii) combine both methods to make up for the remaining amount of virtual currency required for purchase, i.e.,

³¹ More accurately it means a one-way exchange – players can only buy virtual currency using real currency but not the other direction. In this paper, we focus on games that only allow for one-way exchange.

$w - a \cdot k$. Denote the additional playtime that he spends on repeating played gaming stages to earn virtual currency value by t_g .³² Denote the amount of virtual currency value that he gains through the currency exchange by g (hereafter referred to as “purchased amount of virtual currency value”). Eventually, he chooses optimal t_g and g according to the following constrained optimization:

$$\begin{aligned} \mu &= \max_{t_g, g} \{U_P - U_{NP} - c \cdot t_g - g\} \\ \text{s.t. } &\lambda \cdot k \cdot t_g + g \geq w - a \cdot k, t_g \geq 0, g \geq 0 \end{aligned}$$

A player will purchase the module when and only when $\mu \geq 0$.

Denote a player’s optimal choices of t_g and g by t_g^* and g^* . Suppose the player who is indifferent between purchasing and not purchasing the module has time cost \hat{c} , i.e., $\mu|_{c=\hat{c}} = 0$. We denote the provider’s profit from the purchased amount of virtual currency value (hereafter referred to as “currency profit”) by π_g and derive:

$$\pi_g = \int_{\underline{c}}^{\hat{c}} g^* dc.$$

Suppose the provider can also monetize players’ playtime at a time revenue rate r (e.g., through in-game advertising). We denote the provider’s total profit from monetizing players’ playtime (hereafter referred to as “time profit”) by π_T and derive:

$$\pi_T = r \int_{\underline{c}}^{\hat{c}} (t^* + t_g^*) dc.$$

Hence, the provider’s total profit π is:

³² Note that due to the repetitive gameplay, a player’s time cost associated t_g may be higher than that associated with regular playtime t . For example, it includes both the opportunity cost and a utility penalty for repetitive play just to earn virtual currency. The qualitative insights of this paper remain the same after we consider such utility penalty for repetitive gameplay.

$$\pi = \pi_g + \pi_T.$$

The provider chooses the earning rate and the module price to maximize her total profit π .

It is worth mentioning that one example of time profit is advertising-sponsored profit. Suppose the provider publishes ads in the game at a certain level of intensity. For players, the corresponding ad nuisance cost per unit time can be considered as part of their time cost. Specifically, the distribution of players' time cost $c \in [b, 1+b]$ is a distribution that combines ad nuisance cost per unit time and other opportunity cost per unit time. For the provider, the time revenue rate is equivalent to the ad revenue rate.

To avoid technically trivial solutions and meanwhile focus on the game designs that are widely seen in the real world, we assume our parameters to fall into the following ranges. We assume $0 < b < 1/3$ which means that there exist hardcore players with low time cost. We also assume that $0 < a < 1 - 2b$, which means that the free gaming stage makes up a relatively small portion of the entire game. We assume $0 < r < 1 - a - b$ which means that the provider's capability to monetize players' playtime (e.g., through in-game advertising) is not exceedingly high. We restrict the attention to the case $0 < h < (2/3)(\bar{S} - a - 2b)$ where the module's continuation value is less than extreme. Important notations are summarized in Table 5.1.

Table 5.1 Key Model Parameters and Variables

Parameters

- h Module's game continuation value
- k Earning rate
- r Revenue rate from players' playtime
- a Maximum free gaming stage
- c Player's time cost of playing the game
- b Lower bound of players' time cost distribution

Variables

- w Module price in virtual currency value

g	Amount of virtual currency value a player purchases using real currency
t_g	Additional playtime a player spends for earning virtual currency
π	Provider's total profit
π_g	Provider's currency profit
π_T	Provider's time profit

5.2 RESULTS

5.2.1 *Equilibrium analysis*

We first present the players' module purchase decisions and their choices of playtime under different earning rate k and module price w . Note that we forgo the cases where $w - a \cdot k < 0$ because in those cases all players either (i) do not purchase the module, or (ii) purchase the module without spending additional playtime or real currency, i.e., $t_g^* = 0$ and $g^* = 0$. More importantly, the analysis shows that a provider's profit-maximizing k and w will not satisfy condition $w - a \cdot k < 0$ – the provider will at least induce some players to choose $t_g^* > 0$ or $g^* > 0$ in order to maximize her profit. For a similar reason, we also skip presenting the cases where the earning rate is less than the lower bound of players' time cost, i.e., $k < b$. Without loss of generality, we normalize $\lambda = 1$. Unless otherwise stated, we use tilde accents to label equilibrium variables while use hat accents to label thresholds of variables. All proofs of lemmas, propositions and corollaries are included in Appendix E.

Proposition 1 *Players fall into the segments in Table 5.4 based on their time cost c and the provider's choice of earning rate k and module price w . The corresponding optimal choices of t^* , t_g^* , and g^* of each segment are listed in Table 5.3. The expressions of the thresholds in Table 5.4 are:*

$$\hat{w}_B = ak, \hat{w}_{LL} = \frac{h^2}{2} + ak, \hat{w}_{LM} = \left(1 - a - \frac{h}{2} - k\right)h + ak, \hat{w}_{HL} = \frac{h^2k}{2(1-a-h)} + ak, \hat{w}_{HM} = \frac{(1-a-k)^2}{2} + ak,$$

$$\hat{w}_H = \frac{hk}{b} \left(1 - a - b - \frac{h}{2}\right) + ak, \hat{c}_1 = 1 - a - \frac{h}{2} - \frac{w-ak}{h}, \hat{c}_2 = 1 - a - \sqrt{2(w-ak)}, \hat{c}_3 = 1 - a - h,$$

$$\hat{c}_4 = \frac{hk(1-a-h/2)}{w+hk-ak}, \hat{c}_5 = \frac{w+k-2ak - \sqrt{(w-ak)(w+2k-3ak)}}{k}, \text{ and } \hat{k}_B = 1 - a - h.$$

Table 5.2 Players' optimal choices in different player segments

Player segments	Players' optimal choices		
	t^*	t_g^*	g^*
Play to buy limited (PL)	$t^{PL} = a + h$	$t_g^{PL} = (w/k) - a$	$g^{PL} = 0$
Play to buy unlimited (PU)	$t^{PU} = 1 - c$	$t_g^{PU} = (w/k) - a$	$g^{PU} = 0$
Buy to play limited (BL)	$t^{BL} = a + h$	$t_g^{BL} = 0$	$g^{BL} = w - a \cdot k$
Buy to play unlimited (BU)	$t^{BU} = 1 - c$	$t_g^{BU} = 0$	$g^{BU} = w - a \cdot k$
Pure play limited (L)	$t^L = a$	$t_g^L = 0$	$g^L = 0$
Pure play unlimited (U)	$t^U = 1 - c$	$t_g^U = 0$	$g^U = 0$
Not play (NP)	$t^{NP} = 0$	$t_g^{NP} = 0$	$g^{NP} = 0$

Table 5.3 Players' optimal gaming behaviors in different player segments

Player segments	Players' optimal gaming behaviors			
	Finish the free part?	Purchase the module?	Payment method	Finish the premium part?
Play to buy limited (PL)	Yes	Yes	Playtime	Yes
Play to buy unlimited (PU)	Yes	Yes	Playtime	No
Buy to play limited (BL)	Yes	Yes	Currency	Yes
Buy to play unlimited (BU)	Yes	Yes	Currency	No
Pure play limited (L)	Yes	No	–	–
Pure play unlimited (U)	No	No	–	–
Not play (NP)	No	No	–	–

Table 5.4 Player segmentation based on module price w

Case	Earning rate k	Module price w	Player segments in terms of time cost c						
			Play to buy limited (PL)	Play to buy unlimited (PU)	Buy to play limited (BL)	Buy to play unlimited (BU)	Pure play limited (L)	Pure play unlimited (U)	Not play (NP)
L1		Extremely High ($w > \hat{w}_H$)	---	---	---	---	$[b, 1-a]$		
L2	Low ($b < k < \hat{k}_B$)	High ($\hat{w}_{LM} < w \leq \hat{w}_H$)	$[b, \hat{c}_4]$	---	---	---	$[\hat{c}_4, 1-a]$		
L3		Medium ($\hat{w}_{LL} < w \leq \hat{w}_{LM}$)	$[b, k]$	---	$[k, \hat{c}_1]$	---	$[\hat{c}_1, 1-a]$		
L4		Low ($\hat{w}_B < w \leq \hat{w}_{LL}$)	$[b, k]$	---	$[k, \hat{c}_3]$	$[\hat{c}_3, \hat{c}_2]$	$[\hat{c}_2, 1-a]$		
								$[1-a, 1)$	$[1, 1+b]$
H1		Extremely High ($w > \hat{w}_H$)	---	---	---	---	$[b, 1-a]$		
H2	High ($k \geq \hat{k}_B$)	High ($\hat{w}_{HM} < w \leq \hat{w}_H$)	$[b, \hat{c}_4]$	---	---	---	$[\hat{c}_4, 1-a]$		
H3		Medium ($\hat{w}_{HL} < w \leq \hat{w}_{HM}$)	$[b, \hat{c}_3]$	$[\hat{c}_3, \hat{c}_5]$	---	---	$[\hat{c}_5, 1-a]$		
H4		Low ($\hat{w}_B < w \leq \hat{w}_{HL}$)	$[b, \hat{c}_3]$	$[\hat{c}_3, k]$	---	$[k, \hat{c}_2]$	$[\hat{c}_2, 1-a]$		

Proposition 1 shows that in general the players with relatively lower time cost are more likely to buy the module compared to the ones with higher time cost. Because the players with lower time cost are willing to engage in more gameplay, the module will provide greater improvement on gaming utility for them, even though it “unlocks” the same amount of gaming stage h . Specifically, the players with the extremely high time cost (i.e., the not-play segment in Table 5.4) will not purchase the module as they will not even play the game in the first place. Moving down along the time cost, the players in the pure-play-unlimited segment in Table 5.4 will slightly play the game and achieve their unconstrained optimal playtime *before* reaching maximum free gaming stage $S_{NP} = a$. Hence, they will not purchase the module either because they do not need any further gaming stages beyond $S_{NP} = a$. We hereafter refer to such a scenario where a player can eventually achieve his unconstrained optimal playtime $t^U = 1 - c$ as “*unlimited*” gameplay. In contrast, the players in the pure-play-limited segment (e.g., players with $\hat{c}_4 \leq c < 1 - a$ in Case L2 or H2 in Table 5.4) will reach $S_{NP} = a$ before achieving their unconstrained optimal playtime. These players desire more gaming stages, yet they will eventually stop at $S_{NP} = a$ without purchasing the module because the module price is higher than their willingness to pay. We hereafter refer to such a scenario where a player cannot achieve his unconstrained optimal playtime and is capped by either $S_{NP} = a$ or $S_p = a + h$ as “*limited*” gameplay.

The players with further lower time cost will start to purchase the module. Nonetheless, the purchasing players will use different methods to make up the virtual currency they need for purchase. We refer to the choice of using the currency exchange to acquire the module and then continuing to play the game as “*buy-to-play*,” whereas the choice of using the time exchange to do so as “*play-to-buy*.” Recall that the benefit from playing additional playtime t_g is earning $k \cdot t_g$ amount of virtual currency value, while the corresponding cost is $c \cdot t_g$. Hence, to make up for one

unit value in module price w , a player will incur cost of c/k if he uses the time exchange while incur cost of 1 if he uses the currency exchange. For players with $c > k$, the time exchange is more costly and thus he will choose to become a buy-to-play player, i.e., choosing $t_g^* = 0, g^* > 0$. Otherwise, the currency exchange is more costly and thus he will choose to become a play-to-buy player, i.e., choosing $t_g^* > 0, g^* = 0$.

Similar to the pure-play players who do not purchase the module, both the buy-to-play and the play-to-buy players can be further categorized into the unlimited gameplay group and the limited gameplay group depending on if they can eventually realize their unconstrained optimal playtime *after* purchasing the module. For example, players with $\hat{c}_3 \leq c < \hat{c}_2$ in Case L4, after they purchase the module, will realize their unconstrained optimal playtime $t^{BU} = 1 - c$ before reaching the maximum gaming stage $S_p = a + h$. Hence, we refer to them as “buy-to-play-unlimited” players. We summarize all the players’ gaming behaviors in Table 5.3.

Based on players’ module purchase decisions and choices of playtime discussed above, the provider chooses her optimal earning rate and module price according to the following Proposition 2.

Proposition 2 *Depending on time revenue rate r , the provider’s equilibrium choices of earning rate and module price can be divided into the following cases in the table. Note that the last column titled “Segmentation” lists the case of market segmentation which the equilibrium choices will lead to in Proposition 1.*

Case	Time revenue rate	Equilibrium earning rate, module price, and the corresponding provider's profit	Segmentation
1	High ($r > \hat{r}_1$)	$\tilde{k}_1 = \sqrt{br}$, $\tilde{w}_1 = \frac{2}{9}(1-a-2\tilde{k}_1)^2 + a\tilde{k}_1$	L4 or H4 depending on h
2	Medium ($b < r \leq \hat{r}_1$)	$\tilde{k}_2 = \sqrt{br}$, $\tilde{w}_2 = \frac{h}{2}\left(1-a-\frac{h}{2}-2\tilde{k}_2\right) + a\tilde{k}_2$	L3
3	Low ($r \leq b$)	$\tilde{k}_3 = b$, $\tilde{w}_3 = \frac{h}{2}\left(1-a-b-r-\frac{h}{2}\right) + ab$, $\tilde{\pi}_3 = \frac{h}{4(1+r)}\left(1-a-b-r-\frac{h}{2}\right)^2 + \frac{r(a+h)}{2(1+r)}(2-a-2b-h)$	L3 without PL segment

The expressions of the thresholds in the table are $\hat{r}_1 = (2-2a-3h)^2 / (16b)$.

When time revenue rate r is high, i.e., in Case 1 where $r > \hat{r}_1$, the provider focuses more on earning the time profit than the currency profit. Therefore, she wants to minimize the chance that players' unconstrained playtime is capped by $S_p = a + h$. Eventually, she chooses earning rate \tilde{k}_1 and module price \tilde{w}_1 to induce unlimited players, i.e., segment PU and BU in Case L4 or H4, to take the full advantage of the high time revenue rate. When r is medium, i.e., in Case 2 where $b < r \leq \hat{r}_1$, the provider focuses more on earning the currency profit than the time profit. Hence, she chooses \tilde{k}_2 and \tilde{w}_2 to induce limited players, i.e., segment PL and BL in Case L3, whose playtime are capped by $S_p = a + h$. When r is low, i.e., in Case 3 where $r \leq b$, the provider chooses \tilde{k}_3 and \tilde{w}_3 to avoid any play-to-buy players, i.e. shutting down segment PL in Case L3, since the provider cannot extract enough revenue from players' repetitive playtime.

With any of the high, medium or low time revenue rate r , the provider's optimal choice of module price is determined by the margin-volume trade-off between the profit margin from a purchasing player and the total number of purchasing players. What is unique here is that the margin from a purchasing player will be different depending on whether he is a play-to-buy player or a buy-to-play player, and the ratio of play-to-buy ones to buy-to-play ones depends on earning rate k . Specifically, we denote the margin from a buy-to-play player by m^B and that from a play-to-buy player by m^P . According to Table 5.2, we find that

$$m^B = g^* = w_e \text{ and } m^P = r \cdot t_g^* = (r/k)w_e$$

where $w_e \equiv w - a \cdot k$. Hereafter we refer to w_e , i.e., the net amount of virtual currency value a player needs to make up to purchase the module, as *the equivalent price of the module*. The margin ratio $m^P / m^B = r / k$ indicates that a play-to-buy player will generate a higher profit margin than a buy-to-play player when the time revenue rate is greater than the earning rate, i.e., $r > k$. Meanwhile, recall from Proposition 1 that purchasing players with $b < c < k$ will choose to become play-to-buy players, whereas ones with $c > k$ will choose to become buy-to-play ones. As a result, the value of earning rate k will significantly affect where the provider wants to settle the margin-volume trade-off on the demand curve, i.e., her optimal choice of equivalent price w_e^* .

To illustrate the specific impact of earning rate k on optimal equivalent price w_e^* , we consider an initial point where earning rate $k = \hat{k}_1 = b$. As shown in Figure 5.1a, the corresponding optimal equivalent price w_e^* is \hat{w}_{e1} which incurs purchasing volume \hat{d}_1 . When the provider raises the earning rate from \hat{k}_1 to \hat{k}_2 where $b < \hat{k}_2 < r$, it will convert the players in $\hat{k}_1 < c < \hat{k}_2$ from buy-to-play ones to play-to-buy ones. Note that the margin from the emerging play-to-buy players is not only higher than the previous buy-to-play players in the same $\hat{k}_1 < c < \hat{k}_2$, but also increasing at a

higher rate in the equivalent price, i.e., $\partial m^P / \partial w_e > \partial m^B / \partial w_e$. Hence, the provider's previous settling point of the margin-volume trade-off, i.e., point X in Figure 5.1b, is no longer profit-maximizing. The provider has the incentive to raise w_e^* from \widehat{w}_{e1} to \widehat{w}_{e2} , i.e., re-settling the margin-volume trade-off at a more margin-driven position Y, in order to take advantage of both the higher margin as well as the higher marginal rate of margin to price from the emerging play-to-buy players. Although such an increase in the equivalent price will cut down purchasing volume from \widehat{d}_1 to \widehat{d}_2 , the improvement on individual margin of the emerging play-to-buy players in $\widehat{k}_1 < c < \widehat{k}_2$ will overcompensate the loss of volume which cannot be compensated had the players in $\widehat{k}_1 < c < \widehat{k}_2$ stayed as buy-to-play ones. We refer to such overcompensation from the play-to-buy players as *the complementary effect* of the virtual selling strategy.

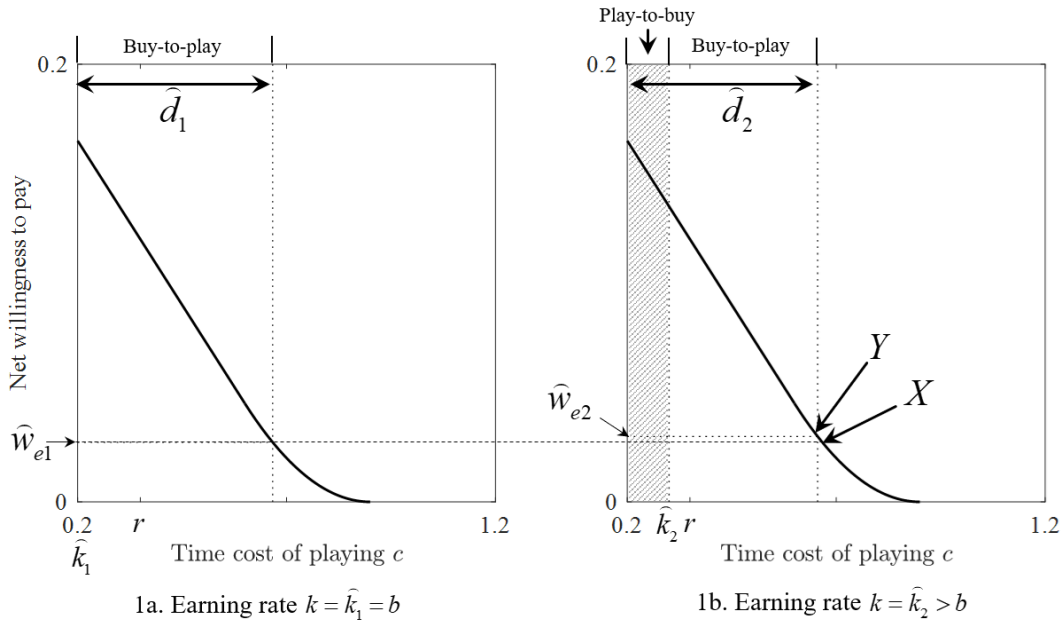


Figure 5.1 Impact of the earning rate on the optimal equivalent price

(Note: This figure is generated based on $b = 0.2$, $r = 0.35$, $a = 0.1$, and $h = 0.3$.)

The complementary effect is powered by (i) the time exchange mechanism which generates the play-to-buy players, and (ii) a sufficient time revenue rate. Note that for each unit of the virtual

currency value a player makes up to purchase the module, the player will generate r/k profit for the provider if he is a play-to-buy one, whereas 1 unit profit if he is a buy-to-play one. The overcompensation takes effect only when time revenue rate $r > k$. Meanwhile, only the players with time cost $b < c < k$ will choose to become play-to-buy players. Hence, the complementary effect exists *only* when time revenue rate $r > b$, i.e., either Case 1 or Case 2 in Proposition 2. It is also worth emphasizing that the existence of the complementary effect also hinges on one particular structure of the gaming market – players with lower time cost not only have higher net willingness to pay for the module, but also at the same time, more likely to become play-to-buy players. Otherwise, had the play-to-buy players had the lower net willingness to pay for the module, they will churn first before the buy-to-play players when the provider raises the equivalent price. In such a case, the provider cannot leverage the overcompensation to enhance her profit.

The overall strength of the complementary effect depends on earning rate k . When k increases, on the one hand, it increases the number of play-to-buy players who will engage in the overcompensation. On the other hand, it also reduces the strength of overcompensation from each play-to-buy player, i.e., r/k . Therefore, the overall strength of the complementary effect will first increase and then decrease in the earning rate, leading both optimal equivalent price w_e^* and optimal profit π^* to exhibit a concave relationship with earning rate k in range $b < k < r$. Eventually, when time revenue rate $r > b$, the provider chooses the profit-maximizing earning rate $\tilde{k} = \sqrt{br}$ where $b < \tilde{k} < r$ as shown in Figure 5.2.

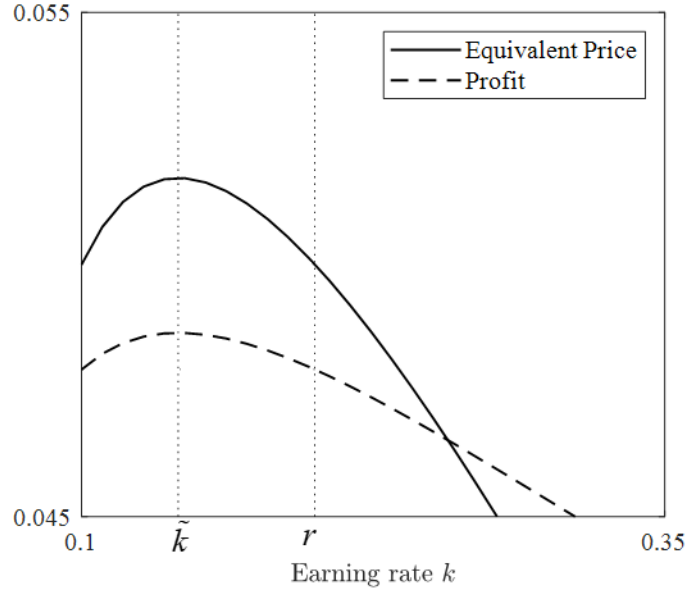


Figure 5.2 The influence of the earning rate k on the equilibrium profit and the optimal equivalent price

(Note: This figure is generated based on $b = 0.1$, $r = 0.2$, $a = 0.1$, and $h = 0.2$.)

5.2.2 Comparison Between the Virtual Selling Strategy and the Real Selling Strategy

In this subsection, we discuss several important differences between the virtual selling strategy and the real selling strategy. A variable with superscript V indicates it is related to the virtual selling strategy whereas one with superscript R indicates it is related to the real selling strategy.

Proposition 3 *The provider is better off, while consumer surplus is worse off with the virtual selling strategy compared to the real selling strategy when the time revenue rate is higher than the lower bound of players' time cost, i.e., $r > b$. For other time revenue rates, both the provider's profit and consumer surplus are identical across two strategies.*

Proposition 3 shows that when time revenue rate $r > b$, players as a whole will be hurt by the virtual selling strategy even though they seem to have an additional way, their playtime, to make the payment for the module compared to the real selling strategy. To explain this surplus reduction, we first note that the real selling strategy can be considered as a special case of the virtual selling

strategy – the case where earning rate k is exogenously fixed at zero. Next, we find that the provider’s optimal equivalent price w_e^{V*} for a given earning rate k does not change when k changes from $k = 0$ to $k = b$ in the virtual selling strategy. The reason is that no player will switch from buy-to-play to play-to-buy when k increases from $k = 0$ to $k = b$, such that the provider has no incentive to change the equivalent price, according to the discussion of Proposition 2. Consequently, in terms of the provider’s optimal profit and the corresponding consumer surplus, the real selling strategy is not only identical to the virtual selling strategy with $k = 0$ but also identical to that with $k = b$. Next, recall from Proposition 2 that due to the complementary effect, the optimal equivalent price is higher at the equilibrium earning rate $k = \tilde{k}$ compared to the rate $k = b$ when time revenue rate $r > b$. Hence, players in general need to make up more monetary value to purchase the module at the market equilibrium of the virtual selling strategy compared to that of the real selling strategy. The provider takes a more margin-driven approach in the virtual selling strategy, focusing on capitalizing on the players with low time cost and thus causing the surplus reduction eventually.

Nonetheless, although players as a whole are worse off, certain players can be better off with the virtual selling strategy, as shown by the following Corollary 1.

When the time revenue rate is moderate, players with time cost $c < \hat{c}_{ww}$ pay less whereas players with time cost $c > \hat{c}_{ww}$ pay more for the module in the virtual selling strategy compared to the real selling strategy.

Proposition 3 and Corollary 1 together indicate a local win-win outcome – both the provider and the players with low time cost are better off with the virtual selling strategy when the time revenue rate is moderate, i.e., $b < r < \hat{r}_{ww}$. Note that in the virtual selling strategy, players with low time cost (e.g., ones with $c < \hat{c}_{ww}$) will become the play-to-buy ones and pay $(c / \tilde{k}) \tilde{w}_e^V$ for the

module. In the real selling strategy, however, they will pay \tilde{w}_e^R . When time revenue rate $r > b$, the equivalent price is higher in the virtual than the real, i.e., $\tilde{w}_e^V > \tilde{w}_e^R$. However, the increment $\tilde{w}_e^V / \tilde{w}_e^R$ is not sufficient to outweigh the discounting factor c / \tilde{k} if (i) the time revenue rate is still below a threshold, i.e., $r < \hat{r}_{ww}$, such that the complementary effect is relatively weak, resulting in only a relatively small increment $\tilde{w}_e^V / \tilde{w}_e^R$, and (ii) the time cost is sufficiently low such that the discounting factor c / \tilde{k} is strong. Eventually, when the time revenue rate is moderate, i.e., $b < r < \hat{r}_{ww}$, those players with time cost $c < \hat{c}_{ww}$ will find $(c / \tilde{k}) \tilde{w}_e^V < \tilde{w}_e^R$, i.e., paying less in the virtual selling strategy than the real selling strategy.

The time exchange which allows players to earn virtual currency value via playtime leads to the discounting factor c / \tilde{k} as well as the local win-win result. It also brings another perhaps interesting observation concerning the virtual selling strategy. Note that in the lens of traditional price discrimination, those players with the lowest time cost are supposed to be charged with the highest price since they have the highest willingness to pay for the module. Yet here, on the contrary, they receive the greatest discount. They only pay $(c / \tilde{k}) \tilde{w}_e^V$ based on their low time cost c , whereas the buy-to-play players who have higher time cost and thus lower willingness to pay have to bear full \tilde{w}_e^V . Such reverse price discrimination is supposed to be detrimental yet proved to be beneficial to the provider's profit. Note that the provider can always set $k = b$ to completely avoid it, yet instead she chooses equilibrium $k = \tilde{k}$ to induce it.

The reason why reverse price discrimination is profit-enhancing here is, again, the time exchange. Specifically, the time exchange transforms players from the provider's direct profit source to her vehicle to draw profit from sponsors (e.g., advertisers). It disconnects how much the

provider earns with how much a player pays. Figure 5.3 shows a detailed breakdown regarding (i) the profit generated by different segments of the players during their acquisition of the module and (ii) their actual payment, i.e., the net utility reduction incurred to acquire the module, in both the virtual selling strategy and the real selling strategy. Note that a play-to-buy player pays $(c/\tilde{k})\tilde{w}_e^V$ yet generates $(r/\tilde{k})\tilde{w}_e^V$ profit, and r is the time revenue rate (e.g. ad revenue rate). The time exchange enables the provider to zero in those players who can draw the time profit from sponsors most efficiently and fully take advantage of them by charging a higher equivalent price. As a result, those players with low time cost, although paying less than other players, contribute to the provider's profit most as shown in Figure 5.3. Eventually, due to the complementary effect that we discussed in Proposition 2, the provider's total profit gets improved, even though with reverse price discrimination.

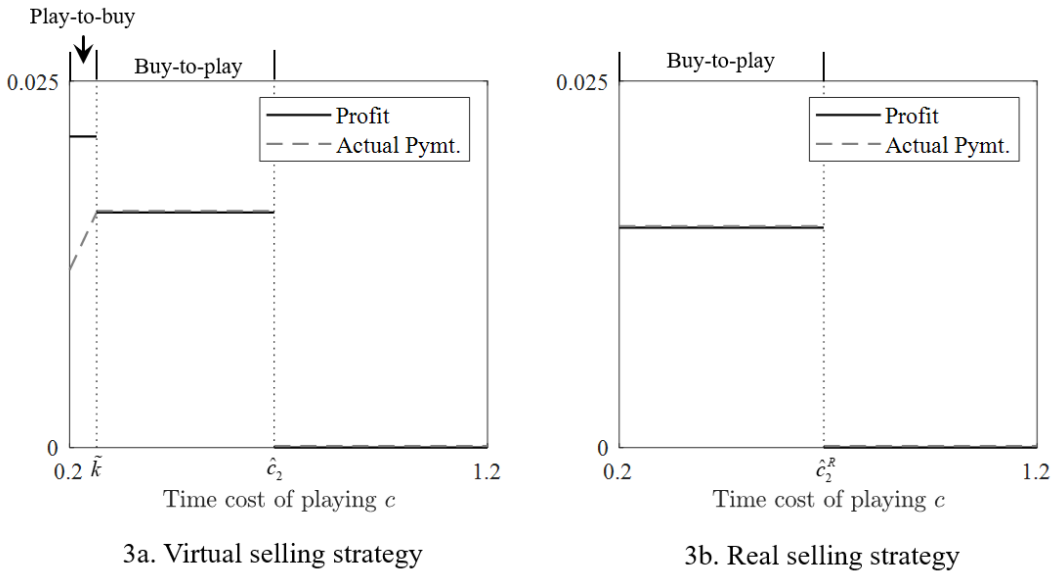


Figure 5.3 The provider's profit and players' actual payment due to the acquisition of the premium module

(Note: This figure is generated based on $b = 0.2$, $r = 0.3$, $a = 0.1$, and $h = 0.1$.)

Proposition 4 *In the real selling strategy, equilibrium module price \tilde{w}^R is decreasing in time revenue rate r . In the virtual selling strategy, equilibrium module price \tilde{w}^V is*

- *decreasing in time revenue rate r when $r < b$;*
- *increasing in time revenue rate r when $r > b$.*

if the module's continuation value h is below a threshold. The threshold of h is a piecewise function of maximum free gaming stage a . Its specific expression is relegated to Appendix E due to its length.

Proposition 4 shows that in the real selling strategy, the equilibrium module price is always decreasing in the time revenue rate – a result consistent with the traditional belief that a content provider shall lower its content price when she can finance the content through in-content ads more efficiently. However, in the virtual selling strategy, the equilibrium module price may have a U-shaped relationship with the time revenue rate when the module's continuation value is low. Figure 5.4 illustrates an example of the U-shaped relationship.

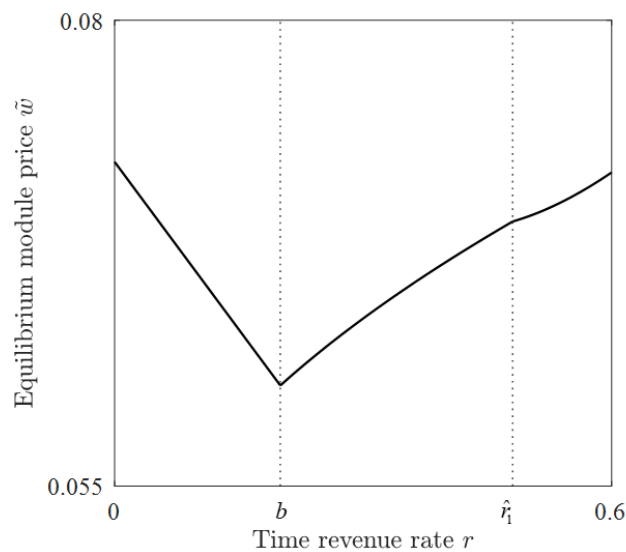


Figure 5.4 Comparative statics of the equilibrium module price with respect to the time revenue rate

(Note: This figure is generated based on $b = 0.2$, $a = 0.2$, and $h = 0.12$.)

The complementary effect plays an important role in forming such a U-shaped relationship. When time revenue rate $r < b$, the time profit is too weak to trigger the complementary effect according to Proposition 2. Consequently, the provider sets equilibrium earning rate $k = \tilde{k}_3 = b$, which degenerates the virtual selling strategy to the real selling strategy. Hence, equilibrium module price \tilde{w}^V decreases in time revenue rate r when $r < b$. When time revenue rate $r > b$, the complementary effect kicks in. According to the result of Proposition 2, the provider will raise the earning rate in response to a higher time revenue rate, i.e., $\partial \tilde{k} / \partial r > 0$ – she wants more players to become play-to-buy players to further boost the overcompensation when she can earn time profit more efficiently. A side effect of raising the earning rate is inflation. Note that with a higher earning rate, the players will carry a higher amount of virtual currency value in their accounts when they reach the maximum free gaming stage, i.e., higher $a \cdot k$. For ease of presentation, we refer to $a \cdot k$ as the coupon value. Recall that the relationship between the coupon value and the equilibrium module price is

$$\tilde{w}^V = \tilde{w}_e^V + a \cdot \tilde{k}.$$

Therefore, the provider has the incentive to inflate equilibrium module price \tilde{w}^V to account for higher $a \cdot \tilde{k}$.

On the other hand, the provider also has the incentive to drop equilibrium equivalent price \tilde{w}_e^V when time revenue rate r increases, i.e., $\partial \tilde{w}_e^V / \partial r < 0$ – she wants to extend the number of purchasing players to focus more on earning time profit than earning currency profit when she can earn time profit more efficiently. The magnitude of the reduction in equilibrium equivalent price \tilde{w}_e^V is moderated by module's continuation value h . When the module only unlocks a few gaming

stages, i.e., h is low, the corresponding equilibrium equivalent price \tilde{w}_e^V is low. For one unit increase in time revenue rate r , the provider will not incur the same, but a less amount of reduction in \tilde{w}_e^V compared to the case where the module unlocks a large number of gaming stages, i.e., h is high, such that equilibrium equivalent price \tilde{w}_e^V is high to begin with. Specifically, we find $\partial^2 \tilde{w}_e^V / \partial r \partial h \leq 0$. Eventually, if a module's continuation value is sufficiently low, the corresponding reduction in the equilibrium equivalent price in response to the higher time revenue rate will also be sufficiently small. It will be outweighed by the rise of the module price due to the provider's motivation to account for inflation, resulting in an overall increase in the equilibrium module price when time revenue rate $r > b$.

5.3 THE EXTENDED MODEL – HETEROGENEOUS GAMING SKILL LEVELS

In this section, we relax the homogenous assumption regarding players' gaming skill levels in the previous analysis. Specifically, we consider two group of players – one with the low level of skill so that they can complete λ_L gaming stages per unit time and the other with the high level of skill so that they can complete λ_H gaming stages per unit time. Note that $\lambda_H > \lambda_L$. The group of players with low skill level λ_L takes d share of the market while the group with high skill level λ_H takes the remaining $1-d$ share. We also assume that $(b+r)/(1-a) < \lambda_L < 1+b$ and $1+b < \lambda_H < (1+b)/(1-a)$. It indicates that within the low-skill group, the players with high time cost will not adopt the game. However, within the high-skill group, the players with high time cost will at least play the free part of the game because of their high skill level.

Proposition 5 *When players' gaming skill levels are heterogeneous, the provider's equilibrium choices of earning rate and module price can be divided into the following cases in the table depending on time revenue rate r .*

Case	Time revenue rate	Equilibrium earning rate and module price
1λ	High ($r > \hat{r}_{1\lambda}$)	$\tilde{k}_{1\lambda} = \sqrt{v/u} \sqrt{br}$, $\tilde{w}_{1\lambda} = \frac{2}{9} (1 - a - 2\tilde{k}_{1\lambda})^2 + a\tilde{k}_{1\lambda}$
2λ	Medium High ($\hat{r}_{2\lambda} < r \leq \hat{r}_{1\lambda}$)	$\tilde{k}_{2\lambda} = \sqrt{v/u} \sqrt{br}$, $\tilde{w}_{2\lambda} = \frac{h}{2} \left(1 - a - \frac{h}{2} - 2\tilde{k}_{2\lambda} \right) + a\tilde{k}_{2\lambda}$
3λ	Medium Low ($b < r \leq \hat{r}_{2\lambda}$)	$\tilde{k}_{3\lambda} = \sqrt{br}/\lambda_H$, $\tilde{w}_{3\lambda} = \frac{h}{2} \left(1 - a - \frac{h}{2} - \eta \right) + a\tilde{k}_{3\lambda}$
4λ	Low ($r \leq b$)	$\tilde{k}_{4\lambda} = b/\lambda_H$, $\tilde{w}_{4\lambda} = \frac{h}{2} \left(1 - a - \frac{h}{2} - \frac{b+r}{u} \right) + ab/\lambda_H$

Note that

$$u = d\lambda_L + (1-d)\lambda_H, \quad v = d\lambda_L^{-1} + (1-d)\lambda_H^{-1}, \quad \text{and} \quad \eta = \frac{d}{u}(b+r) + \frac{1-d}{u}(2\sqrt{br}).$$

The expressions of the thresholds in the table are

$$\hat{r}_{1\lambda} = \frac{(2-2a-3h)^2 u}{16b} \frac{1}{v}, \quad \hat{r}_{2\lambda} = \frac{u}{v} \frac{b}{\lambda_L^2}.$$

The expression of the profit is relegated to Appendix E due to its length.

Proposition 5 shows the provider's equilibrium choice of earning rate and module price when the players' gaming skill levels are heterogeneous. Note that Proposition 5 will convert to Proposition 2 when we set $\lambda_L = 1$ and $d = 1$. A notable difference between the results of the heterogeneous case (i.e., Proposition 5) and the ones of the homogenous case (i.e., Proposition 2) is the emergence of an interim case – Case 3λ in Proposition 5 – where only the high-skill group has play-to-buy players. No player in the low-skill group will use the time exchange to purchase

the module because they cannot earn virtual currency value fast enough due to their inadequate gaming skill. Case 3λ becomes the market equilibrium when the time revenue rate is medium low, i.e., $b < r \leq \hat{r}_{2\lambda}$. Under such an insufficient time revenue rate, the provider will find it overall unprofitable to adopt a high earning rate to induce play-to-buy players in the low-skill group because although it may boost the profit from the low-skill group, it eventually causes greater damage on the profit from the high-skill group due to excessive provisioning of virtual currency value.

When the time revenue rate turns to be sufficient, i.e., $r > \hat{r}_{2\lambda}$, both groups will have play-to-buy players in the equilibrium. Hence, the equilibrium earning rate and module price of Case 1λ and 2λ are qualitatively the same as the ones in Case 1 and 2 of Proposition 2, except the equilibrium earning rate in the heterogeneous case is factored by $\sqrt{v/u}$ which depends on the distribution of the players' gaming skill levels. The distributional factor $\sqrt{v/u}$ will lead to the following properties in the heterogeneous case.

Corollary 2 *With a sufficient time revenue rate, i.e., $r > \hat{r}_{2\lambda}$, the equilibrium earning rate under the heterogeneous skill levels is decreasing in the market share of the high-skill group.*

On the one hand, the low-skill players will induce the provider to choose a high earning rate. It is because such players are reluctant to use the time exchange to purchase the module due to their limited ability to proceed in the game. Hence, the provider will choose a high earning rate to compensate for their low skill level, such that a portion of the players will become play-to-buy players to boost the provider's profit. On the other hand, the high-skill players will induce the provider to adopt a low earning rate. It is because such players can earn the virtual currency value needed for purchase in a very short period of playtime due to their superior gaming skill. Hence, they will not generate sufficient time profit unless the provider sets a low earning rate to prolong

their playtime spent on acquiring the module. The balance between the two countervailing forces determines the equilibrium earning rate. When there is a greater percentage of the high-skill players on the market, the provider will choose a lower earning rate to better gain profit from the expanding high-skill group. She eventually forgoes the profit from the low-skill group, because the size of the group is diminishing.

Corollary 3 *The following results still hold under the heterogeneous skill levels.*

- *The provider is better off, while consumer surplus is worse off with the virtual selling strategy compared to the real selling strategy when the time revenue rate is higher than the lower bound of players' time cost, i.e., $r > b$.*
- *The equilibrium module price in the virtual selling strategy is first decreasing and then increasing in the time revenue rate if the module's continuation value is below a threshold.*

One of the main reasons why this paper's qualitative results still hold under the heterogeneous skill levels is that, as we previously discussed, the provider can use the earning rate to factor in the influence of players' skill levels. Given such a property, the provider's choice of the equilibrium module price will not be directly affected by players' skill levels but only indirectly through the earning rate. Due to the preservation of the relationship between the equilibrium module price and the earning rate, the complementary effect still exists in the presence of heterogeneous players' skill levels. Eventually, the complementary effect leads to the same profit augmentation, the surplus reduction, and the U-shaped relationship between the equilibrium module price and the time revenue rate, as it does in the homogeneous case.

5.4 CONCLUSION AND DISCUSSION

The virtual selling strategy reshapes players' optimal decisions on their playtime and module purchases by offering players an additional method to acquire the module – the time exchange.

The players who choose such a method to purchase the module – the play-to-buy players – contribute to the provider’s profit differently from the buy-to-play players who purchase the module via the currency exchange. We address such difference through identifying the undocumented complementary effect. The complementary effect makes the play-to-buy players have higher marginal rate of margin to price compared to the buy-to-play players when the time revenue rate is above a threshold. The provider will therefore further target on the play-to-buy players, charging a higher equivalent price of the module to extract greater profit from them. Consequently, the buy-to-play players will suffer from the price increase. Overall, compared to the real selling strategy, the virtual selling strategy might increase the provider’s profit, which provides one alternative explanation for the market reality that many providers adopt the strategy. However, due to the rise of the equivalent price, players as a whole might be hurt by the virtual selling strategy even though they are provided with an additional way, i.e., the time exchange, to pay for the module.

It is worth noting that the specific condition for the virtual selling strategy to benefit the provider and to hurt consumer surplus is that the time revenue rate is higher the lower bound of players’ time cost. It is equivalent to say that there exists at least one player whose cost of playing the game for one unit of time is lower than the amount of profit that the provider can retrieve from that unit of playtime. The virtual selling strategy can effectively zero in those players with low time cost and then exploit the gap between how much they pay for their gameplay and how much the provider can earn from their gameplay. The real selling strategy cannot do so. The condition also implies that for a given time revenue rate, players will prefer the real selling strategy over the virtual selling strategy if the game is sufficiently attractive to them, or in other words, their time cost of playing the game is sufficiently low.

This work also provides pricing suggestions for providers in the gaming industry. We show that a provider might want to raise the module price when the time revenue rate increases, or in other words, when she becomes more efficient in monetizing players' playtime. This perhaps interesting result is attributed to the complementary effect we identified in this study. Specifically, the complementary effect will lead to inflation when the time revenue rate increases, such that the provider wants to increase the module price to account for the inflation. When the time revenue rate is sufficiently high, inflation becomes so strong that the provider's incentive to raise the module price to account for the inflation outweighs her incentive to reduce the module price to expand the market adoption of the premium module.

In this study, we assume that there is no uncertainty in players' valuation towards a module's value. We argue that players who consider purchasing the module are familiar with the game and can accurately estimate the value of the module. In reality, however, players may be still uncertain about the value of a premium module even though they have played the free version. Meanwhile, this study does not consider the potential network effect which often exists in multiplayer games – we narrow down the scope to the type of games which do not exhibit strong network effects. We acknowledge not incorporating the valuation uncertainty and the network effect as the limitation of this study and leave them for future research.

Chapter 6. CONCLUDING REMARKS

The development of the digital economy has posed a significant influence on people's everyday life. The change in consumer behavior and the supplier's decision has motivated the online platforms to adopt various policies to encourage users' participation, promote market efficiency, and pursue profit improvement. In my dissertation, I explored the impact of online platform policies and monetization strategies using three different settings. My first essay examines the influence of inspection picture disclosure on the consumers' decisions in a sharing economy platform. My second work analyzes how the peer-based monetary incentive would influence the content generation behavior in a user-generated content social platform. My third work investigates the freemium pricing method using virtual selling strategy in free-to-play games. The three works reflect the impact of the digital economy on the consumers' decision, supplier's behavior, and the firm's strategy, correspondingly.

The tremendous growth of the sharing economy has reshaped the consumer's information seeking and purchase behavior. My first work investigates how consumers would process the platform disclosed picture information and make their purchase decisions accordingly. By showing the negative impact of image disclosure on the supplier with a relatively low hygiene quality, I emphasize that images that appropriately describe the suppliers' quality can lead to more efficient market outcomes, whereas the noise in pictures can hurdle the efficiency. Moreover, by showing the moderation effect of other mechanisms, such as reputation and competition, on the effectiveness of picture disclosure, this work integrates the role of consumer, supplier, and platform-side enforcement in the sharing economy ecosystem, and, in the meantime, helps the platform owners to prioritize their inspection process. The techniques, such as text-mining,

computer-vision, and deep-learning methods can help with the platform's decision by better targeting the suppliers. It can also reduce the labor cost by automating the image selection process.

The UGC platforms, such as Twitter, Reddit, and Twitch, have both gained popularity and achieved high profit, thanks to the contribution of the content generators. My second work studies the influence of peer-based monetary incentive on user-generated content production. The results indicate that the monetary incentive voluntarily provided by peers can effectively motivate content generation and increase the content quality. It extends the understanding of how monetary incentive would influence prosocial behavior by showing that "who provides the incentive" and the "quality contingency" address the concern of the crowd-out effect of monetary incentive. The analysis of the heterogeneous impact on latent content generator groups can help the platform to target the group that is more reactive to the social and monetary incentives.

My third work is based on the setting of free-to-play games, a category that generates the majority of the revenue of the mobile game industry. I examine how the virtual selling strategy, the method broadly applied by the free-to-play games, leads to different market outcomes from the traditional real selling strategy, where players can purchase the premium module using real currency directly only. The results indicate that, due to the undocumented complementary effect, the virtual selling strategy can benefit the provider even though it provides a time discount to the players, and hurt the consumer surplus even though it offers an extra purchase method. The effect also shows that the relationship between the equilibrium module price and the time revenue rate follows a U-shape, which contradicts the traditional result, and can help the game provider with their pricing decisions.

My dissertation intends to serve two purposes. First, I aim to understand both the impact and the underlying mechanisms of the platform strategies and policies. The innovative business

implementations offer a chance to investigate the new tradeoffs and extend the understanding of established theories. Second, I combine different methods to obtain valid explanations and to further enhance the business insights. As more information is delivered in unstructured form, these techniques help to keep up with the rapid-developing online platform practices.

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APPENDIX A: INSPECTION CHECKLIST

We provide a scanned version of the inspection checklist that the inspectors follow during the procedure in Figure A.1. We cover the home cook's name, the inspector's name and corresponding signature.

家厨食品安全指导书

Name		Date		大部分是		大部分不是		完全不是	
Location		Date		大部分是		大部分不是		完全不是	
地址	姓名	日期	时间	得分	备注	得分	备注	得分	备注
厨房卫生	厨房卫生	3	整体橱柜、嵌入式燃气灶、油烟机管道	1		4	排油烟机可止漏元件标准装配	3	
		5	2个以上燃气灶	5		6	洗菜池不锈钢材质或陶质材料	3	
		7	有完整的厨房用具(消毒柜、油烟机、冰柜/冰箱、燃气灶、高压锅、电饭煲等厨房必备设备)	3		8	符合厨房入驻标准	1	
		9	排油烟机、灶台外观整洁干净无油垢	5		10	橱柜整体及边角均无污迹、油渍	5	
		11	管道无油渍、污迹、锈迹等	5		12	洗菜池内外干净无垢、外观清洁不粘腻	5	
		13	冰箱、冰柜等外观干净无污迹、门把手不粘垢、内部无异味	3		14	高压锅、电饭煲、铁锅封口袋等机器无油垢或污迹	3	
		15	客厅、厨房物品摆放有序不杂乱	3		16	客厅、厨房门窗、地板、墙体清洁明亮、天花板、角落无蜘蛛丝等明显卫生死角	1	
		17	地板无油垢、污迹、积水、烟头、烟灰、墙面无油垢及污迹	5		18	未见活体苍蝇、老鼠、蟑螂、蚂蚁或其尸体、(若有宠物)设置脚踏、有效防止宠物进入厨房	3	
		19	食材、餐盒、盛装食材器皿等必须清洗干净,不使用清洁球(钢丝球),可用紫色3M那高白洁布替代	3		20	洗手间及洗手间周边禁止出现任何食材及食物器皿且禁止清洗任何菜品及器皿	5	
		21	厨房与卫生间非紧邻并相互独立,且卫生间门随时关闭	4		22	抹布无异味、不油腻、刀具及砧板干净整洁,有抹布、刀具存放区,便于晾干	1	
		23	垃圾桶无蚊蝇滋生,外观清洁不粘腻,每两个小时倾倒一次垃圾	3		24	食品、熟食、油桶不可接触地面,需离地10公分	3	
		25	大米、面粉等食材不使用密封口或掩盖,避免异物虫子掉入(可放置于橱柜中)	3		26	食材的色泽及新鲜度:食材无生水/风干/发霉等	3	
		27	食品的保存管理计分:食品及调料密封(如盖或保鲜膜)	3		28	所有大米、油品、面粉皆有生产许可或质量安全(蓝色QS)认证,且未过期,过期应立即处理掉	5	
家厨个人	个人形象	29	年龄18-60周岁且做饭是本人	1		30	衣裤无异味及污迹,穿着围裙,戴头罩	5	
		31	家厨无传染性疾病、精神疾病、无犯罪前科、未加入邪教组织、恐怖组织等	1					

食品安全卫生总分: 84分

Suggestions and Comments

回家吃饭食品
工作人员签字

Figure A.1 The Checklist for Hygiene Inspection

The checklist specifies 31 items that cover three major aspects: (1) the home cook's hygiene habit, (2) the hygiene condition of the kitchen in general, and (3) the hygiene and condition of the

cooking facilities. The home cook's hygiene habit includes the chef's dressing code, personal credit, and criminal history, etc.

We list several items for each aspect. The hygiene of the kitchen covers the ingredient's storage, quality, and freshness, the location of the kitchen, the hygiene of kitchenware such as pot, pan, knives, plates, and the hygiene of floor and ceiling. The hygiene of the cooking facilities includes the condition of the stove, vent, cabinet, fridge, and the sink. Each item is allocated a score to help determine the home cook's final hygiene grade shown in the attached column.

APPENDIX B: THE ROOMNET DEEP LEARNING PROCEDURE

In this section, we detail the functionality and construction of the encoder and decoder subnetwork as well as the optimization objective. The network architecture is summarized in Figure 2 to help with explanation. We also provide the qualitative result of the RoomNet prediction of test data.

Encoder Network

The encoder network consists of 13 convolutional layers which correspond to the first 13 convolutional layers in VGG16 network for object classification Russakovsky et al. (2015). Batch normalization and an element-wise rectified-linear non-linearity (ReLU) $\max(0, x)$ is applied in each convolutional layer. The encoder will map the input image to lower resolution feature maps. Different from object classification task, to be memory efficient, the max-pooling *indices*, i.e. the locations of the maximum value in each pooling window, are stored before the sub-sampling, in order to memorize the boundary information for segmentation.

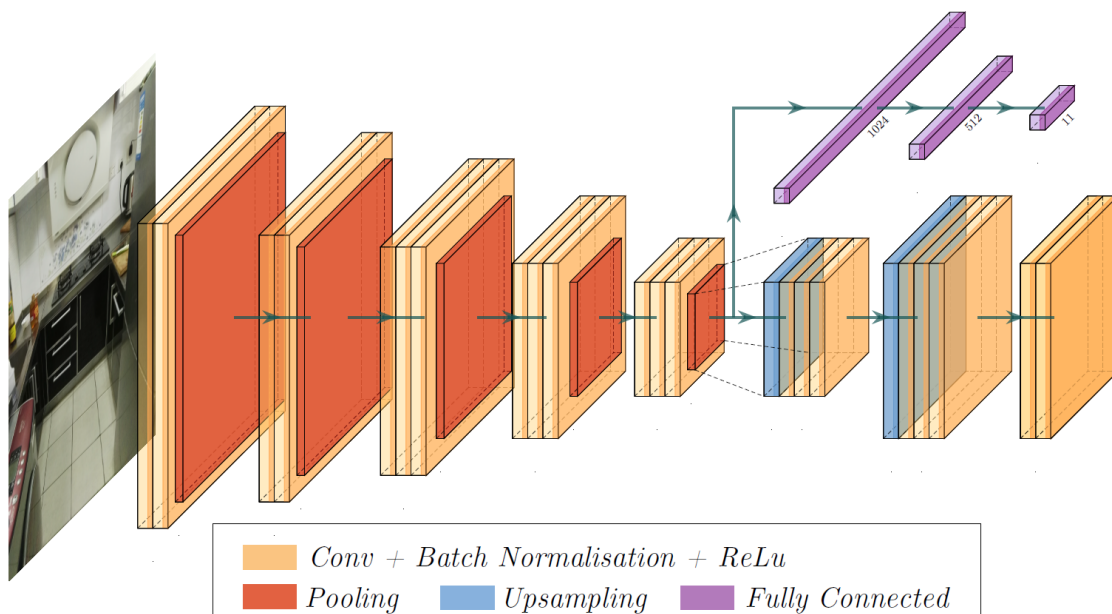


Figure B.1 An Illustration of the RoomNet Architecture

Decoder Network

The decoder in this network non-linearly upsamples its input feature maps using max-pooling indices stored in the pooling steps. The upsampled maps are then convoluted with trainable filters to produce dense feature map. The output is a set of 2D room layout keypoints used for recovery of the 3D room layout structure. The outputs are of the dimensions 40×40 instead of full resolution 320×320 to reduce memory usage during training and testing.

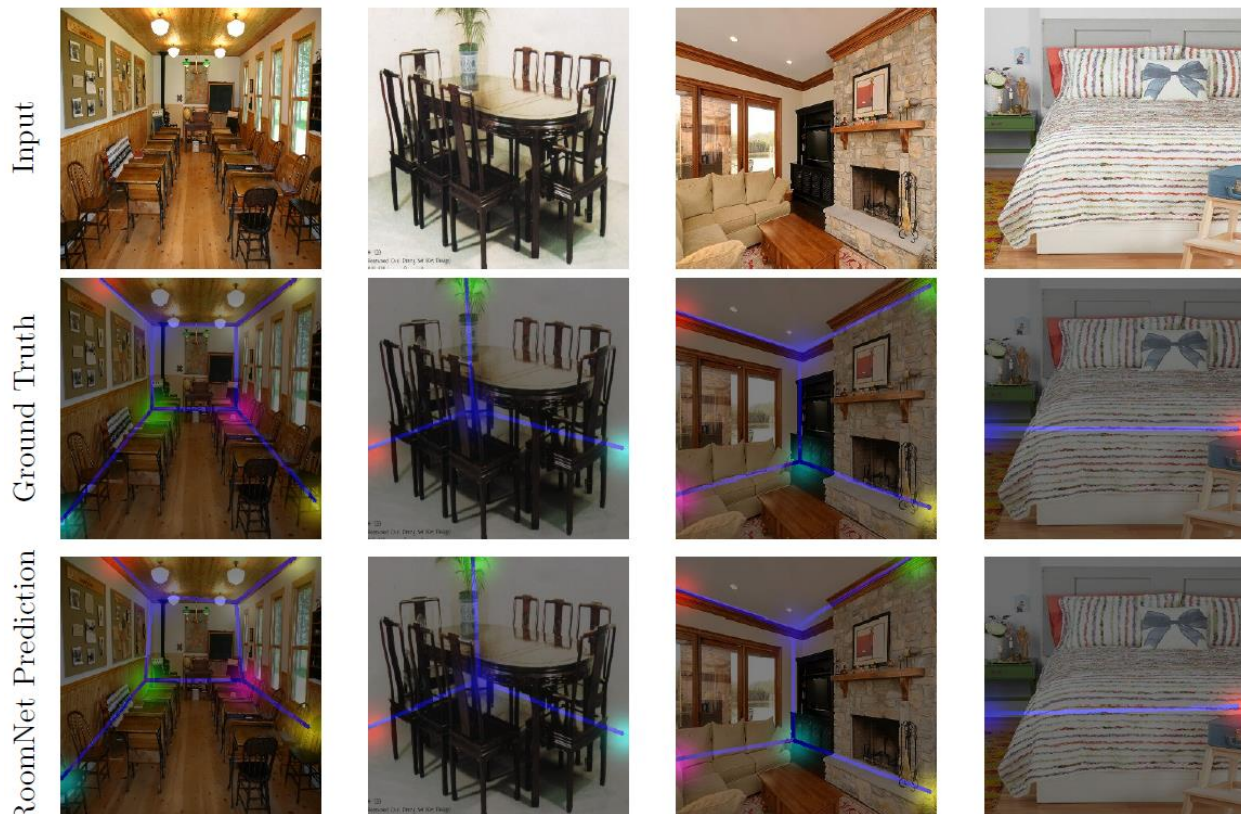


Figure B.2 The RoomNet Predictions and the Ground Truth

Given the keypoint regressor from the decoder sub-network and the room type classifier from the side head layer, the final optimization objective is a loss function that linearly combines the Euclidean loss for the regressor and the cross-entropy loss for the room type prediction. By taking into account both the layout type and the 2D keypoints of each type, the bottleneck layer was

enforced to implicitly model the information regarding the keypoints that encode the 2D structure of the room layout.

We show the qualitative results of the RoomNet prediction of test data in the LSUN dataset in Figure 3. The first row is the input images, the second row is the ground truth with each keypoint represented by a 2D Gaussian heatmap centered on the true keypoint location, and the third row is the predicted keypoint heatmap by connecting predicted keypoints in the corresponding order specified by the predicted room type. As reported by Lee et al. (2017), the prediction accuracy is well satisfactory.

APPENDIX C: THE SUPPLEMENTARY INFORMATION FOR THE APPLICATION OF AMAZON MECHANICAL TURK

APPENDIX C.1: THE LAYOUT OF AMT SURVEY

In below, we provide two figures to show the survey design posted on AMT.

Task Instructions: Section A (Click to expand)

There are two sections in this task. Please read the instruction for each task carefully before completing your task.


In Section A below, you will be given one image of a kitchen. Suppose this kitchen provides food delivery service. Based on the image, choose the attitude that best fits your feelings, from "strongly disagree" to "strongly agree".

If the image does not contain enough information for you to express your attitude, please:

- First check "Not shown on image" checkbox.
- Then still select your attitude based on your own inference.

Section A: Attitude Survey

Kitchen Image



I have seen closed kitchens before: Yes No

I am a full time worker:

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Not Shown on image
--	-------------------	----------	---------	-------	----------------	--------------------

Generally speaking, I feel the kitchen has a good hygiene quality.

I feel comfortable ordering food from this kitchen.

	High	Medium	Low
--	------	--------	-----

If I am asked to rate the hygiene quality of the kitchen from "High" to "Low", I will give:

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Not Shown on image
--	-------------------	----------	---------	-------	----------------	--------------------

When ordering delivery/pickup, I do not care if the kitchen image is posted or not.

The condition of cooking facilities (e.g., vent, stove, fridge, etc.) is satisfactory.

The kitchenware (e.g., pot, pan, etc.) is clean.

I think the food ingredients are properly stored.

The overall layout of the kitchen (e.g., floor, table, etc.) looks clean.

	Strongly Negatively	Negatively	Not Influenced	Positively	Strongly Positively
--	---------------------	------------	----------------	------------	---------------------

The image feature (e.g., light, angle) influenced my attitude towards hygiene quality. (Strongly negative means the feature gives a very bad impression.)

Figure C.1 AMT Layout for Section A

Task Instructions: Section B (Click to expand)

In Section B below, you will be given 9 kitchen images. Categorize them into three groups based on your feeling of hygiene level. Class A has the highest hygiene quality, C has the lowest hygiene quality.

Please note that:

- All images need to be classified
- Each image can be classified only once
- You do NOT need to divide the images evenly into the groups.

Section B: Image Categorization

Kitchen 1



Kitchen 2



Kitchen 3



Kitchen 4



Kitchen 5



Kitchen 6



Kitchen 7



Kitchen 8



Kitchen 9



Classify the above images into three groups. Class A has the highest hygiene level, C has the lowest level. ALL IMAGES need to be categorized. Each image can be classified to one and only one class.

	Kitchen 1	Kitchen 2	Kitchen 3	Kitchen 4	Kitchen 5	Kitchen 6	Kitchen 7	Kitchen 8	Kitchen 9
Class A Kitchens	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Class B Kitchens	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Class C Kitchens	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Figure C.2 AMT Layout for Section B

In the first image, we include one image and a set of questions asking about the detail of the hygiene quality. In the second image, we include 9 images and let users to categorize the images into three hygiene groups.

APPENDIX C.2: CONSISTENCY OF RESULTS COLLECTED FROM AMT

In this section, we check if the perceived hygiene quality we collected is reasonable. If the data collected is proper, the result from Section A should be similar to that from Section B. Since we collect multiple perceived hygiene result for each home cook's kitchen image from both Section A and Section B, we first calculate the mean and variance of perceived hygiene quality collected from Section A and Section B for each home cook. We then compare the results using two methods.

First, for each home cook, we calculate the difference in mean from Section A and Section B, and test if the difference in mean is significantly different from zero. We find that the difference in mean is not significant at 5% level for both home cooks with hygiene grade A and C (with t-statistics equal to 1.70 and 0.72, respectively), while the result is significant for those with hygiene grade B. Since the difference in mean is 0.069, which is a small amount compared to the 0-2 scale, we consider the difference acceptable. Below we also include the Figure 5a below to demonstrate the distribution of the difference in means.

Second, for each home cook, we test if the difference in the mean of perceived hygiene grade is significantly different from zero. We are able to do this because for each home cook under each section, we have several perceived hygiene grade record, and are therefore able to calculate the corresponding mean and variance. We find that the test statistics for over 80% of the home cooks is not significantly different from zero. And we consider it as a valid evidence that the results collected from the two sections are consistent.

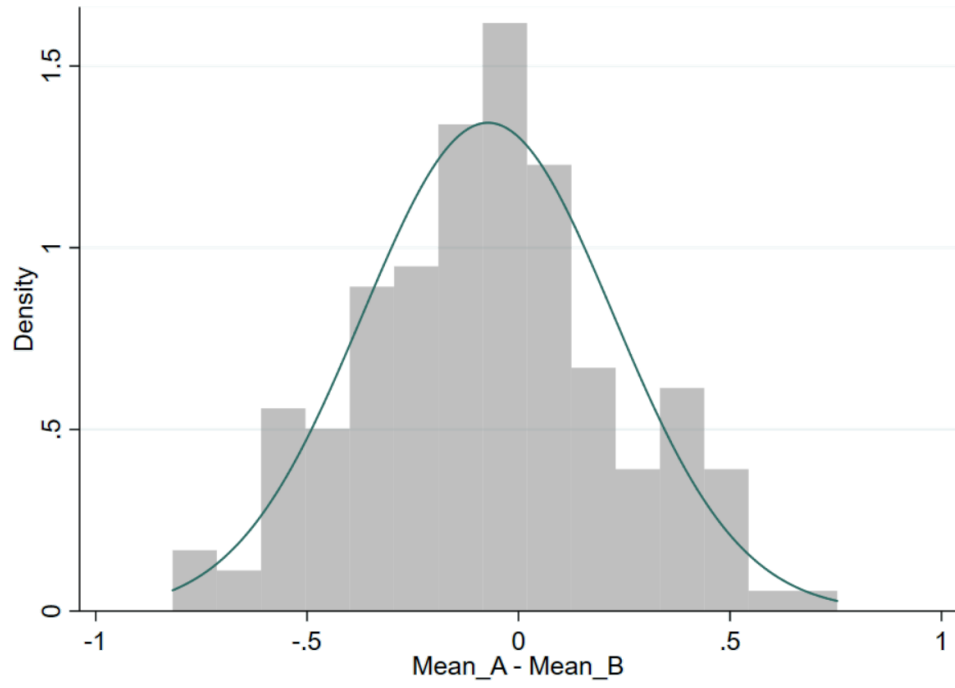


Figure C.3 Difference in the Mean of Perceived Hygiene Grade

APPENDIX D: THE SUPPLEMENTARY INFORMATION FOR UNSTRUCTURED DATA PROCESSING

APPENDIX D.1: KEYWORDS FOR COMMENT TOPICS

In this section, we provide the keywords used to identify each comment sentiment. We define 12 comment topics with respect to delivery and food quality. For each topic, we collect the frequent words appeared in the comments and extend the word base as described in Section 4.2 in the paper. We then refine the keywords through a feature selection procedure so that we do not include topic-irrelevant keywords. The specific topic, corresponding variable construction and the keywords are presented in Table 1 below.

Table D.1 Keywords under Each Topic

Topic	Variable	Keywords
Punctuality	Senti_Punc	Late, early, on time
Communication	Senti_Cmu	Communicate, active, talk
Service Quality	Senti_Svc	Attitude, five-star, service, kind, considerate
Pack of Food	Sent_Box	Spill, broken, open, paper, leak, box, bag
Food Temperature	Sent_Warm	Cold, warm
Navigation	Senti_Loc	Wrong place, navigation, lost
Hygiene Quality	Senti_Hyg	Fresh, clean, freshly, hair, smell, stinky, healthy, smelly, spoiled
Well Cooked	Senti_Cook	Over cooked, under cooked
Seasoning	Senti_Season	Oily, spicy, salty, greasy, heavy, heat
Dish Flavor	Senti_Flavor	Authentic, home, hometown, childhood, mom, miss, flavor,
Food Quantity	Senti_Quant	Quantity, full, sides, enough, set
Discount	Senti_Gift	Gift, deal, free

APPENDIX D.2: FEATURE SUMMARY

In this section, we provide summary statistics in Table 2 for features constructed based on unstructured data, including comment sentiment on different topics, dish style proportion, and dish style count.

Table D.2 Summary Statistics for Comment and Dish Style Features

Variable	Description	Min	Max	Med	Mean	S.D.
<i>Sentiment Features</i>						
Senti_Punc	Punctuality of delivery	0	2.00	1.43	1.443	0.379
Senti_Cmu	Communication skills	0	2.00	0.00	0.284	0.644
Senti_Svc	Service quality	0	2.00	1.73	1.706	0.298
Senti_Box	Dishes are properly packed	0	2.00	1.80	1.729	0.313
Senti_Warm	Temperature of the dish delivered	0	2.00	1.79	1.741	0.289
Senti_Loc	Navigation of delivery	0	1.00	0.00	0.006	0.079
Senti_Hyg	Hygiene quality	0	2.00	1.70	1.664	0.329
Senti_Cook	Dishes are properly cooked	0	1.00	0.00	0.018	0.126
Senti_Season	Dishes are properly seasoned	0	2.00	1.68	1.646	0.381
Senti_Flavor	Flavor of the dishes	0	2.00	1.67	1.628	0.370
Senti_Quant	Quantity of the dishes	0	2.00	1.61	1.593	0.375
Senti_Gift	Gifts and deals	0	2.00	1.75	1.702	0.314
<i>Dish Percentage</i>						
PCT_Dimsum	Percentage of dimsum dish	0	1.00	0.17	0.243	0.215
PCT_Noodle	Percentage of noodle dish	0	0.67	0.08	0.082	0.064
PCT_Meat	Percentage of meat dish	0	0.67	0.10	0.103	0.078
PCT_Veggie	Percentage of vegetable dish	0	0.60	0.11	0.117	0.079
PCT_Soup	Percentage of soup dish	0	0.69	0.08	0.096	0.086
PCT_FryStew	Percentage of stir-fried and stew dish	0	0.90	0.32	0.309	0.021
<i>Dish Count</i>						
Dimsum	Number of dimsum dish offered	0	54.00	7.00	9.989	9.802
Noodle	Number of noodle dish offered	0	27.00	3.00	4.002	3.649
Meat	Number of meat dish offered	0	43.00	4.00	5.347	5.300
Veggie	Number of vegetable dish offered	0	45.00	5.00	6.081	5.679
Soup	Number of soup dish offered	0	78.00	3.00	4.912	6.031
StirFry_Stew	Number of stir-fried dish or stews offered	0	127.00	13.00	15.860	13.186

APPENDIX D.3: THE MODERATION EFFECT OF DIFFERENT SENTIMENT MEASURES

Several measures can be applied to represent the consumers' sentiment towards a supplier's hygiene quality. Apart from using the review ratings, another standard approach is to use the sentiment extracted from the whole consumers' comment. Below, we show the moderation effect of the reputation mechanism using three measures (1) review rating, (2) comment sentiment, and (3) hygiene-specific sentiment.

Table D.3 Reputation Mechanism and Platform Disclosure

Variables	(1) Review Star		(2) Comment Sentiment		(3) Hyg Sentiment	
RVW_STR×Disclosure	-0.036	(0.141)				
Cmt_Sent×Disclosure			0.018	(0.146)		
Hyg_Sent×Disclosure					-0.201*	(0.107)
Disclosure	0.295	(0.687)	0.087	(0.128)	0.451**	(0.183)
Revit-1	0.398***	(0.006)	0.398***	(0.006)	0.398***	(0.006)
Observations	23,570		23,570		23,570	
Other Controls	-Included-		-Included-		-Included-	
Time FE	Y		Y		Y	

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.0$. Standard error in brackets

We do not observe a moderation effect when reputation is measured using review rating or comment sentiment, as both measures fail to capture the consumers' attitude towards the specific hygiene aspect. Using the aspect-based sentiment analysis, on the other hand, better identifies the sentiment towards hygiene quality.

APPENDIX D.4: BALANCE CHECK FOR CONTINGENT FACTOR

One concern for the analysis of multiple mechanisms is that, if the inspection decision (i.e., the treatment assignment) depends on the factors included in the interaction term, then the estimation could be biased. In this section, we construct a balance check on these factors to show that the assignment is balanced. The result is reported in Table 3 below.

Table D.4 Balance Check for Contingent Factors

<i>Contingent Features</i>	Before Match				After Match			
	Mean		t-test		Mean		t-test	
	Control	Treatment	t	p-value	Control	Treatment	t	p-value
Cpt_Ratio	0.219	0.169	10.863	0.000	0.174	0.174	-0.124	0.901
HHI	0.035	0.010	7.125	0.000	0.012	0.012	-0.192	0.848
RVW_STR	4.880	4.840	2.570	0.010	4.860	4.840	0.834	0.404
Hyg_Sent	1.509	1.438	4.316	0.000	1.473	1.452	0.752	0.452

APPENDIX E: PROPOSITION PROOF FOR CHAPTER 5

PROOF OF PROPOSITION 1

When the module is acquired through virtual currency, player c first optimizes his purchase strategy (t_g, g) by solving following constrained optimization problem:

$$\begin{aligned} \mu &= \max_{t_g, g} \{U_P - U_{NP} - c \cdot t_g - g\} \\ \text{s.t. } &k \cdot (t_g + a) + g \geq w, t_g \geq 0, g \geq 0 \end{aligned}$$

and he will purchase the module if and only if $\mu \geq 0$. Let $\delta = U_P - U_{NP}$. Note that for a player with $c > 1 - a$, his optimal gameplay is $t^* = 1 - c$ and is realized before reaching $S = a$, and he has: $\delta = U_P - U_{NP} = U|_{t=1-c} - U|_{t=1-c} = 0$. Thus, $\mu < 0$ is true for all $c > 1 - a$, indicating that these players will never purchase the module.

Players' optimal utility with and without purchase is shown below:

$$U_i = \max_t \{L - c \cdot t\} = \max_t \{S - S^2/2 - c \cdot t\}, i \in \{P, NP\} \text{ where } S = \begin{cases} t & \text{if } t \leq S_i \\ S_i & \text{if } t > S_i \end{cases}$$

We solve for the players' optimal playtime and the corresponding gaming utility. The result is:

$$U_P = \begin{cases} U|_{t^*=a+h} & \text{if } b < c \leq \hat{c}_3 \\ U|_{t^*=1-c} & \text{if } \hat{c}_3 < c \leq 1-a \end{cases} \text{ and } U_{NP} = U|_{t^*=a}.$$

where $\hat{c}_3 = 1 - (a + h)$. Let $\delta_1 = U|_{t^*=a+h} - U_{NP}$ and $\delta_2 = U|_{t^*=1-c} - U_{NP}$, we find the marginal cost to generate one unit of virtual currency value through real currency exchange is:

$$|MC_g| = \left| \frac{\partial(\delta_i - ct_g - g)}{\partial g} \right| / \left| \frac{\partial(k \cdot (t_g + a) + g)}{\partial g} \right| = 1, \text{ and the marginal cost through time exchange is}$$

$$|MC_{t_g}| = \left| \frac{\partial(\delta_i - ct_g - g)}{\partial t_g} \right| / \left| \frac{\partial(k \cdot (t_g + a) + g)}{\partial t_g} \right| = \frac{c}{k} \text{ for } i \in \{1, 2\}. \text{ As players' time cost } c \geq b, \text{ we know that}$$

if earning rate $k \leq b$, $c \geq k$ is always true and that $|MC_g| \leq |MC_{t_g}|$ holds for all $c \in [\underline{c}, \bar{c}]$. Thus, we have

$t_g^* = 0$ for all players. For later analysis, we forgo this scenario and consider only the case when $k > b$.

Consider two cases: optimizing $\{\delta_1 - c \cdot t_g - g\}$ for players with $b < c \leq \hat{c}_3$ and optimizing $\{\delta_2 - c \cdot t_g - g\}$

for players with $\hat{c}_3 < c \leq 1 - a$. Construct the Lagrangian, where:

$$L_i = \delta_i - c \cdot t_g - g + \lambda_1 \cdot (k \cdot t_g + g + a \cdot k - w) + \lambda_2 \cdot t_g + \lambda_3 \cdot g, \quad i \in \{1, 2\}.$$

Solving for $\{t_g^*, g^*\}$, we have:

$$\left\{ t_g^* = \frac{w}{k} - a, g^* = 0 \right\} \text{ when } \{c \leq k, w > ak\},$$

$$\left\{ t_g^* = 0, g^* = w - ak \right\} \text{ when } \{k < c < 1 - a, w > ak\}, \text{ and}$$

$$\left\{ g^* = 0, t_g^* = 0 \right\} \text{ when } w \leq ak.$$

We then solve the conditions for $\mu \geq 0$. First combine players' optimal purchase decision with their optimal

choices of gameplay. Let $\hat{k}_B = 1 - a - h$ and $\hat{w}_B = ak$, we have:

$$(1.1) \left\{ t_g^* = \frac{w}{k} - a, g^* = 0, t^* = 1 - c \right\} \text{ if } \{\hat{c}_3 < c \leq k, k \geq \hat{k}_B, w > \hat{w}_B\},$$

$$(1.2) \left\{ t_g^* = \frac{w}{k} - a, g^* = 0, t^* = a + h \right\} \text{ if } \{c \leq k, k < \hat{k}_B, w > \hat{w}_B\} \text{ or } \{c \leq \hat{c}_3, k \geq \hat{k}_B, w > \hat{w}_B\},$$

$$(2.1) \left\{ t_g^* = 0, g^* = w - ak, t^* = 1 - c \right\} \text{ if } \{c > k, k \geq \hat{k}_B, w > \hat{w}_B\} \text{ or } \{c > \hat{c}_3, k < \hat{k}_B, w > \hat{w}_B\},$$

$$(2.2) \left\{ t_g^* = 0, g^* = w - ak, t^* = a + h \right\} \text{ if } \{k < c \leq \hat{c}_3, k < \hat{k}_B, w > \hat{w}_B\},$$

$$(3.1) \left\{ t_g^* = 0, g^* = 0, t^* = a + h \right\} \text{ if } \{c \leq \hat{c}_3, w \leq \hat{w}_B\}, \text{ and}$$

$$(3.2) \left\{ t_g^* = 0, g^* = 0, t^* = 1 - c \right\} \text{ if } \{c > \hat{c}_3, w \leq \hat{w}_B\}.$$

We forgo Cases (3.1) and (3.2) since no player will engage in extra time or currency effort to obtain the

module. For each of the rest cases, we calculate a price upper bar \bar{w} , above which no player will purchase

the module; and a price lower bar \underline{w} , below which all players with time cost $c < 1 - a$ will purchase. When price falls between the two boundaries, we solve for the marginal player \hat{c} who is indifferent between purchase and not purchase, and players will purchase only if their time cost $c < \hat{c}$. Combining all cases mentioned, we have results shown in Proposition 1.

PROOF OF PROPOSITION 2

The provider chooses the combination of (w, k) to maximize $\pi = \pi_g + \pi_T$, where $\pi_g = \int_{\underline{c}}^{\hat{c}} g^* dc$ and $\pi_T = r \int_{\underline{c}}^{\bar{c}} (t^* + t_g^*) dc$. We first solve for the equilibrium price assuming the earning rate is given. We then solve for the optimal earning rate conditional on the equilibrium price. Lastly, we examine if the result achieves the local optimal point by checking the Hessian matrix.

Equilibrium Price

From Proposition 1, we know that a price higher than \hat{w}_H (Case L1, H1) cannot be an equilibrium because no player will purchase the module given the price. If the module price is lower than \hat{w}_B , the profit does not depend on price. Consider each of the rest price region, we calculate the corresponding profit and find that for case H4, L4 and L3, the profit is concave in w , explicitly,

$$\frac{\partial^2 \pi_{H4}}{\partial w^2} = \frac{\partial^2 \pi_{L4}}{\partial w^2} = -\frac{3(w-ak)}{(1+r)(2(w-ak))^{3/2}} \text{ and } \frac{\partial^2 \pi_{L3}}{\partial w^2} = -\frac{2}{(1+r)h}.$$

For case H3, H2 and L2, the profit decreases in price, that is,

$$\frac{\partial \pi_{H3}}{\partial w} = \frac{\partial \pi_{H2}}{\partial w} = \frac{\partial \pi_{L2}}{\partial w} = -\frac{rb}{(1+r)k}.$$

For case H4, L4 and L3, we calculate the first order condition and solve for the optimal price. For case H4 and L4, we have equilibrium price and the corresponding profit:

$$\tilde{w}_{1k} = \frac{2}{9} \left(1 - a - k - \frac{br}{k} \right)^2 + ak, \text{ and } \tilde{\pi}_{1k} = \frac{2}{27(1+r)} \left(1 - a - k - \frac{br}{k} \right)^3 + \frac{r(a+h)}{2(1+r)} (2 - a - 2b - h),$$

and for case L3, we have equilibrium price and the corresponding profit:

$$\tilde{w}_{2k} = \frac{h}{2} \left(1 - a - \frac{br}{k} - \frac{h}{2} - k \right) + ak, \text{ and } \tilde{\pi}_{2k} = \frac{h}{4(1+r)} \left(1 - a - k - \frac{br}{k} - \frac{h}{2} \right)^2 + \frac{r(a+h)}{2(1+r)} (2 - a - 2b - h).$$

We further solve for the market conditions that the optimal price is compatible with the corresponding price region. The optimal price $w_k^* = \tilde{w}_{1k}$ is valid under either of the market conditions below:

i. $r \leq b$ and $h \geq \hat{h}_1 = \frac{2(1-a-b-r)}{3}$;

ii. $h < \hat{h}_1$ and $k \geq \hat{k}_1 = \frac{1}{4} \left(2 - 3h - 2a + \sqrt{(2 - 2a - 3h)^2 - 16br} \right)$;

iii. $r > b$ and $h \geq \hat{h}_2 = \frac{2}{3} (1 - a - 2\sqrt{br})$;

iv. $r > b$, $k < \hat{k}_2 = \frac{1}{4} \left(2 - 3h - 2a - \sqrt{(2 - 2a - 3h)^2 - 16br} \right)$ and $\hat{h}_1 \leq h < \hat{h}_2$;

v. $r > b$, $\hat{h}_1 \leq h < \hat{h}_2$, and $k \geq \hat{k}_1$.

Under those market conditions, the profit increases in w if $w < \tilde{w}_{1k}$ and decreases in w otherwise. The optimal price $w^* = \tilde{w}_{2k}$ is valid under market conditions: (i) $h < \hat{h}_1$ and $k < \hat{k}_1$; (ii) $r \geq b$, $\hat{h}_1 \leq h < \hat{h}_2$, and $\hat{k}_2 \leq k < \hat{k}_1$. Similarly, the profit increases in w if $w < \tilde{w}_{2k}$ and decreases in w otherwise. Note also that the profit increases in w under the region $(\hat{w}_B, \hat{w}_B + \varepsilon)$ and the profit does not depend on w if $w \leq \hat{w}_B$.

Thus, a price lower than \hat{w}_B cannot be an optimal choice.

Optimal Earning Rate Given the Optimal Price \tilde{w}_{1k} and \tilde{w}_{2k}

For Case H4 and L4, we have:

$$\frac{\partial \tilde{\pi}_{1k}}{\partial k} = \frac{2A^2}{9k^4(1+r)} (br - k^2), \text{ where } A = ak + br + k^2 - k < 0.$$

Thus, we have an interior solution $\tilde{k}_1 = \sqrt{br}$, and the corresponding price $\tilde{w}_1 = \frac{2}{9} (1 - a - 2\sqrt{br})^2 + a\sqrt{br}$.

We then check the Hessian matrix to see if we obtain local maximum. The leading principal minors are:

$$\left| \frac{\partial^2 \pi_1(\tilde{w}_1, \tilde{k}_1)}{\partial w^2} \right| = - \frac{3(\tilde{w}_1 - a\tilde{k}_1)}{(1+r)(2\tilde{w}_1 - 2a\tilde{k}_1)^{3/2}} < 0;$$

$$\begin{vmatrix} \frac{\partial^2 \pi_1(\tilde{w}_1, \tilde{k}_1)}{\partial w^2} & \frac{\partial^2 \pi_1(\tilde{w}_1, \tilde{k}_1)}{\partial w \partial k} \\ \frac{\partial^2 \pi_1(\tilde{w}_1, \tilde{k}_1)}{\partial k \partial w} & \frac{\partial^2 \pi_1(\tilde{w}_1, \tilde{k}_1)}{\partial k^2} \end{vmatrix} = \frac{(1-a-2\sqrt{br})}{\sqrt{br}(1+r)^2} > 0.$$

The Hessian matrix is negative semi-definite. Thus, the equilibrium result $(\tilde{w}_1, \tilde{k}_1)$ is the local maximum.

We then revisit the feasible region for $(\tilde{w}_1, \tilde{k}_1)$. First, \tilde{k}_1 falls in the feasible region only when $r > b$ and

when $h \geq \hat{h}_2$. When $r \leq b$, the provider will choose the minimum earning rate possible, i.e., $\tilde{k}_1^b = r$, and

$\tilde{w}_1^b = \frac{2}{9}(1-a-b-r)^2 + ab$ when $h < \hat{h}_1$. When $h < \hat{h}_2$, the provider will choose either \hat{k}_1 or \hat{k}_2 .

Similarly, for Case L3, we have:

$$\frac{\partial \tilde{\pi}_{2k}}{\partial k} = \frac{h}{4k^3(1+r)}(br - k^2)(2k - 2ak - 2br - hk - 2k^2).$$

We have three sets of solutions for optimal \tilde{k} and corresponding \tilde{w} :

$$\left\{ \tilde{k}_2 = \sqrt{br}, \tilde{w}_2 = \frac{h}{2} \left(1 - a - \frac{h}{2} - 2\sqrt{br} \right) + a\sqrt{br} \right\},$$

$$\left\{ \tilde{k}_2^{h1} = \frac{1}{2} - \frac{a}{2} - \frac{h}{4} + \frac{\sqrt{(2-2a-h)^2 - 16br}}{4}, \tilde{w}_2^{h1} = \tilde{w}_{2k} \Big|_{k=\tilde{k}_2^{h1}} \right\},$$

$$\left\{ \tilde{k}_2^{h2} = \frac{1}{2} - \frac{a}{2} - \frac{h}{4} - \frac{\sqrt{(2-2a-h)^2 - 16br}}{4}, \tilde{w}_2^{h2} = \tilde{w}_{2k} \Big|_{k=\tilde{k}_2^{h2}} \right\},$$

where $\tilde{k}_2^{h1}, \tilde{k}_2^{h2}$ exist iff $(2-2a-h)^2 > 16br$. As for Hessian Matrix, we have:

$$\left| \frac{\partial^2 \pi_2}{\partial w^2} \right| = -\frac{2}{(1+r)h} < 0 \text{ for all feasible } (w, k);$$

$$\left| \begin{array}{cc} \frac{\partial^2 \pi_2(\tilde{w}_2, \tilde{k}_2)}{\partial w^2} & \frac{\partial^2 \pi_2(\tilde{w}_2, \tilde{k}_2)}{\partial w \partial k} \\ \frac{\partial^2 \pi_2(\tilde{w}_2, \tilde{k}_2)}{\partial k \partial w} & \frac{\partial^2 \pi_2(\tilde{w}_2, \tilde{k}_2)}{\partial k^2} \end{array} \right| = \frac{(1-a-(h/2)-2\sqrt{br})}{4\sqrt{br}(1+r)^2} > 0 \text{ if } h < \hat{h}_2.$$

Thus, $(\tilde{w}_2, \tilde{k}_2)$ is the local maximum point when $h < \hat{h}_2$.

Check the other two sets of results. Let $x = 2 - 2a + h$. The other results exist iff $x^2 > 16br > 0$. The

determinants of the Hessian matrix are:

$$\left| \frac{\frac{\partial^2 \pi_2(\tilde{w}_2^{h1}, \tilde{k}_2^{h1})}{\partial w^2}}{\frac{\partial^2 \pi_2(\tilde{w}_2^{h1}, \tilde{k}_2^{h1})}{\partial k \partial w}} \quad \frac{\frac{\partial^2 \pi_2(\tilde{w}_2^{h1}, \tilde{k}_2^{h1})}{\partial w \partial k}}{\frac{\partial^2 \pi_2(\tilde{w}_2^{h1}, \tilde{k}_2^{h1})}{\partial k^2}} \right| = \frac{8(x^2 - 16br)(8br - x^2 - x\sqrt{x^2 - 16br})}{(1+r)^2(x + \sqrt{x^2 - 16br})^4} < 0, \text{ and}$$

$$\left| \frac{\frac{\partial^2 \pi_2(\tilde{w}_2^{h2}, \tilde{k}_2^{h2})}{\partial w^2}}{\frac{\partial^2 \pi_2(\tilde{w}_2^{h2}, \tilde{k}_2^{h2})}{\partial k \partial w}} \quad \frac{\frac{\partial^2 \pi_2(\tilde{w}_2^{h2}, \tilde{k}_2^{h2})}{\partial w \partial k}}{\frac{\partial^2 \pi_2(\tilde{w}_2^{h2}, \tilde{k}_2^{h2})}{\partial k^2}} \right| = \frac{8(x^2 - 16br)}{(-x + \sqrt{x^2 - 16br})^4(1+r)^2} (x\sqrt{x^2 - 16br} - (x^2 - 8br)) < 0.$$

The corresponding Hessian matrix is not negative semi-definite, and therefore, $(\tilde{w}_2^{h1}, \tilde{k}_2^{h1})$ and $(\tilde{w}_2^{h2}, \tilde{k}_2^{h2})$ are not the local maximum point. Similarly, when $r \leq b$, the provider will choose the minimum earning

rate possible, i.e., $\tilde{k}_2^b = r$, and $\tilde{w}_2^b = \frac{h}{2} \left(1 - a - \frac{h}{2} - b - r \right) + ab$.

Putting All Cases Together

i. When $r > b$ and $h \geq \hat{h}_2$:

$$\tilde{k}_1 = \sqrt{br}, \tilde{w}_1 = \frac{2}{9}(1 - a - 2\sqrt{br})^2 + a\sqrt{br}, \tilde{\pi}_1 = \frac{2(1 - a - 2\sqrt{br})^3}{27(1+r)} + cst;$$

ii. When $r > b$ and $h < \hat{h}_2$:

$$\tilde{k}_2 = \sqrt{br}, \tilde{w}_2 = \frac{h}{2} \left(1 - a - \frac{h}{2} - 2\sqrt{br} \right) + a\sqrt{br}, \tilde{\pi}_2 = \frac{h}{4(1+r)} \left(1 - a - \frac{h}{2} - 2\sqrt{br} \right)^2 + cst;$$

iii. When $r \leq b$ and $h \geq \hat{h}_1$:

$$\tilde{k}_1^b = r, \tilde{w}_1^b = \frac{2}{9}(1 - a - b - r)^2 + ab, \tilde{\pi}_1^b = \frac{2(1 - a - b - r)^3}{27(1+r)} + cst;$$

iv. When $r \leq b$ and $h < \hat{h}_1$:

$$\tilde{k}_2^b = r, \tilde{w}_2^b = \frac{h}{2} \left(1 - a - \frac{h}{2} - b - r \right) + ab, \tilde{\pi}_2^b = \frac{h}{4(1+r)} \left(1 - a - b - r - \frac{h}{2} \right)^2 + cst,$$

where $cst = r(a+h)(2-a-h-2b)/(2(1+r))$.

For better interpretation of the role of earning rate r , we re-parameterize the result such that the feasible regions for each set of equilibrium results are expressed in terms of r only. In particular, we let $\hat{h}_2 = f(r)$

. The, we have the updated boundary: $\hat{r}_1 = f^{-1}(h) = (2-2a-3h)^2/(16b)$. Recall that we focus on the region where $h \leq \frac{2}{3}(1-a-2b)$. Therefore, we have:

i. When $r > \hat{r}_1$: $\tilde{k}_1 = \sqrt{br}$, $\tilde{w}_1 = \frac{2}{9}(1-a-2\sqrt{br})^2 + a\sqrt{br}$, $\tilde{\pi}_1 = \frac{2u}{27}(1-a-x)^3 + cst$;

ii. When $b < r \leq \hat{r}_1$: $\tilde{k}_2 = \sqrt{br}$, $\tilde{w}_2 = \frac{h}{2}\left(1-a-\frac{h}{2}-2\sqrt{br}\right) + a\sqrt{br}$, $\tilde{\pi}_2 = \frac{h}{4(1+r)}\left(1-a-\frac{h}{2}-2\sqrt{br}\right)^2 + cst$;

iii. When $r \leq b$: $\tilde{k}_3 = r$, $\tilde{w}_3 = \frac{h}{2}\left(1-a-\frac{h}{2}-b-r\right) + ab$, $\tilde{\pi}_3 = \frac{h}{4(1+r)}\left(1-a-b-r-\frac{h}{2}\right)^2 + cst$.

Notably, when $h < \hat{h}_3 = \frac{2}{3}\left(1-a-2\sqrt{(1-a-b)b}\right)$, we have $\hat{r}_1 > 1-a-b$ and only case ii and iii are valid.

PROOF OF PROPOSITIONS 3

Profit Comparison

First we solve the optimal profit under real selling, where virtual currency generation is not allowed. Players with $c = \hat{c}_2^R = 1 - a - \sqrt{2p}$ are indifferent between no purchase and buy-to-play unlimited. Players with

$c = \hat{c}_1^R = 1 - a - \frac{h}{2} - \frac{p}{h}$ are indifferent between no purchase and buy-to-play limited. Buy-to-play unlimited

players exist only when $p < \hat{p}_1 = h^2/2$. Players will purchase only when $p < \hat{p}_H = h(1 - a - (h/2) - b)$.

We solve for the optimal price under each price condition. Let π_1^R be the profit when $p \leq \hat{p}_1$ and π_2^R be

the profit when $\hat{p}_1 < p < \hat{p}_H$. We have second order condition satisfied, with $\frac{\partial^2 \pi_1^R}{\partial p^2} = -\frac{3\sqrt{2}}{4\sqrt{p}(1+r)} < 0$ and

$\frac{\partial^2 \pi_2^R}{\partial p^2} = -\frac{2}{h(1+r)} < 0$. We then solve $\frac{\partial \pi_1^R}{\partial p} = 0$ and $\frac{\partial \pi_2^R}{\partial p} = 0$ to obtain the optimal price, the

corresponding feasible region, as well as the optimal profit. The results are:

i. When $h > \hat{h}_1$, then $\tilde{p}_1^R = \frac{2}{9}(1 - a - b - r)^2$ and $\tilde{\pi}_1^R = \frac{2(1 - a - b - r)^3}{27(1+r)} + cst$;

ii. When $h \leq \hat{h}_1$, then $\tilde{p}_2^R = \frac{h}{2}\left(1 - a - \frac{h}{2} - b - r\right)$ and $\tilde{\pi}_2^R = \frac{h}{4(1+r)}\left(1 - a - \frac{h}{2} - b - r\right)^2 + cst$.

Consistent with intuition, the optimal profit is the same as that under virtual selling when $r \leq b$. The optimal price equals the equivalent price under virtual selling when $r \leq b$. In other words, virtual selling degenerates to real selling when $r \leq b$.

We know that when $r \leq b$, the profit of virtual and real selling is the same. Below consider $r > b$ only.

First, we can easily show that $\hat{h}_1 = \frac{2}{3}(1 - a - b - r) < \frac{2}{3}(1 - a - 2\sqrt{br}) = \hat{h}_2$. Thus, we compare:

i. $\tilde{\pi}_1^R = \frac{2(1 - a - 2\sqrt{br})^3}{27(1+r)} + cst$ and $\tilde{\pi}_1^R = \frac{2(1 - a - b - r)^3}{27(1+r)} + cst$ when $h > \hat{h}_2$;

$$\text{ii. } \tilde{\pi}_2 = \frac{h}{4(1+r)} \left(1 - a - \frac{h}{2} - 2\sqrt{br} \right)^2 + cst \text{ and } \tilde{\pi}_2^R = \frac{h}{4(1+r)} \left(1 - a - \frac{h}{2} - b - r \right)^2 + cst \text{ when } h \leq \hat{h}_1;$$

$$\text{iii. } \tilde{\pi}_2 = \frac{h}{4(1+r)} \left(1 - a - \frac{h}{2} - 2\sqrt{br} \right)^2 + cst \text{ and } \tilde{\pi}_1^R = \frac{2(1-a-b-r)^3}{27(1+r)} + cst \text{ when } \hat{h}_1 < h \leq \hat{h}_2,$$

where $cst = r(a+h)(2-a-h-2b)/(2(1+r))$. For later analysis, we compare $\hat{\pi} = (1+r)(\tilde{\pi} - cst)$.

Define $\pi_1^x = \frac{2}{27}(1-a-x)^3$, and $\pi_2^x = \frac{h}{4} \left(1 - a - \frac{h}{2} - x \right)^2$ as functions of x . We have $\frac{\partial \pi_1^x}{\partial x} < 0$, $\frac{\partial \pi_2^x}{\partial x} < 0$.

Note that $\hat{\pi}_1 = \pi_1^x(2\sqrt{br})$, $\hat{\pi}_1^R = \pi_1^x(b+r)$, $\hat{\pi}_2 = \pi_2^x(2\sqrt{br})$, and $\hat{\pi}_2^R = \pi_2^x(b+r)$. Besides, $b+r > 2\sqrt{br}$

when $r > b$. Thus, for case i and ii, we have $\hat{\pi}_1 > \hat{\pi}_1^R$ and $\hat{\pi}_2 > \hat{\pi}_2^R$. As for case iii, note that $\frac{\partial \hat{\pi}_2}{\partial h} > 0$ when

$h \leq \hat{h}_2$ and $\frac{\partial \pi_1^x}{\partial h} = 0$ for all feasible h . When $\hat{h}_1 < h \leq \hat{h}_2$, as h increases, $\hat{\pi}_2$ increases, but $\hat{\pi}_1^R$ stays

constant. Furthermore, we know that when $h = \hat{h}_1$, $\hat{\pi}_1^R = \hat{\pi}_2^R$ and $\hat{\pi}_2 > \hat{\pi}_2^R$. Therefore, we have $\hat{\pi}_2 > \hat{\pi}_1^R$

when $\hat{h}_1 < h \leq \hat{h}_2$. Formally, we have:

$$\hat{\pi}_1^R \Big|_{\hat{h}_1 < h \leq \hat{h}_2} = \hat{\pi}_1^R \Big|_{h=\hat{h}_1} = \hat{\pi}_2^R \Big|_{h=\hat{h}_1} < \hat{\pi}_2 \Big|_{h=\hat{h}_1} = \hat{\pi}_2 \Big|_{h=\hat{h}_1} < \hat{\pi}_2 \Big|_{\hat{h}_1 < h \leq \hat{h}_2}.$$

Combining three cases, we know that the profit under virtual selling is greater than that under real selling when $r > b$. The two profits are the same when $r \leq b$.

Consumer Surplus

Denote consumer surplus under virtual selling, a function of price and earning rate, as: CS_1 and CS_2 . Let

$$CS_1 = CS_1(\tilde{w}_1, \tilde{k}_1), \quad CS_2 = CS_2(\tilde{w}_2, \tilde{k}_2), \quad CS_1^b = CS_1(\tilde{w}_1^b, \tilde{k}_1^b), \quad CS_2^b = CS_2(\tilde{w}_2^b, \tilde{k}_2^b).$$

The degeneration feature implies that the consumer surplus under real selling is the same as that under virtual selling with

$r \leq b$, i.e., $CS_2^b = CS_2^R$ when $h \leq \hat{h}_1$ and $CS_1^b = CS_1^R$ when $h > \hat{h}_1$. For later analysis, we consider $r > b$,

and use CS^b to represent the corresponding CS^R .

Recall that $\hat{h}_1 < \hat{h}_2$, we then compare:

i. CS_2 with CS_2^b when $h \leq \hat{h}_1$. Let $\Delta CS_2 = CS_2^b - CS_2$;

ii. CS_1 with CS_1^b when $h > \hat{h}_2$. Let $\Delta CS_1 = CS_1^b - CS_1$;

iii. CS_2 with CS_1^b when $\hat{h}_1 < h \leq \hat{h}_2$.

Case i: $\Delta CS_2 = \sqrt{r}(\sqrt{b} - \sqrt{r})^3(2a + h) + tmp$, where $tmp = 6r(b - \sqrt{br}) + br(b - 2r) + r^3 + 2r^2 - 2b\sqrt{br}$.

ΔCS_2 decreases in $(2a + h)$, whose maximum value is $2(1 - b - r)$. Under this condition, we are able to show that $\Delta CS_2 > 0$ holds for all feasible (b, r) . Thus, $CS_2^b > CS_2$ when $h \leq \hat{h}_1$.

Case ii: similar to case i, we have $\frac{\partial^2 \Delta CS_1}{\partial a^2} < 0, \frac{\partial \Delta CS_1}{\partial a} < 0, \frac{\partial \Delta CS_1}{\partial h} = 0$. Thus, when $a = 1 - b - r$, ΔCS_1

achieves its minimum value which is greater than zero. Thus, $CS_1^b > CS_1$ when $h > \hat{h}_2$.

Case iii: similar to the logic for profit comparison, we know that $\frac{\partial CS_1^b}{\partial h} = 0$ and $\frac{\partial CS_2}{\partial h} > 0$. Note that when

$h > \hat{h}_2$, $CS_1^b > CS_1$ and when $h = \hat{h}_2$, $CS_1 = CS_2$. That is:

$$CS_1^b \Big|_{\hat{h}_1 < h < \hat{h}_2} = CS_1^b \Big|_{h = \hat{h}_2} = CS_1^b \Big|_{h > \hat{h}_2} > CS_1 \Big|_{h > \hat{h}_2} = CS_2 \Big|_{h = \hat{h}_2} > CS_2 \Big|_{\hat{h}_1 < h < \hat{h}_2}$$

Therefore, when $\hat{h}_1 < h \leq \hat{h}_2$, $CS_1^b > CS_2$.

Combining three cases, we know that the consumer surplus under virtual selling is lower than that under real selling when $r > b$. The consumer surplus under the two strategies are the same when $r \leq b$.

PROOF OF COROLLARY 1

We first solve for the actual payment of each group of players under virtual and real selling strategy.

In real selling, all players who adopt the premium content will pay $Pmt^R = (h/2)(1-a-b-h/2-r)$.

In virtual selling, players will pay the same amount as real selling if $r \leq b$ due to the degeneration feature.

Otherwise, when $b < r < \hat{r}_1$,

$$\text{Players with } b < c < k \text{ will pay } \frac{c}{\sqrt{br}} \cdot \frac{h}{2} \left(1 - a - \frac{h}{2} - 2\sqrt{br} \right);$$

$$\text{Players with } k \leq c \leq \frac{1}{2} \left(1 - a - \frac{h}{2} + 2\sqrt{br} \right) \text{ will pay } \frac{h}{2} \left(1 - a - \frac{h}{2} - 2\sqrt{b}\sqrt{r} \right),$$

Furthermore, when $r \geq \hat{r}_1$ is feasible, then:

$$\text{Players with } b < c < k \text{ will pay } \frac{c}{\sqrt{br}} \cdot \frac{2(1-a-2\sqrt{br})^2}{9};$$

$$\text{Players with } k \leq c \leq \frac{1}{3} (1-a+2\sqrt{br}) \text{ will pay } \frac{2(1-a-2\sqrt{br})^2}{9};$$

Comparing the corresponding cases, we find that:

When $r \geq \hat{r}_1$ is feasible, there exist players who can pay less in virtual selling, compared to real selling, if

the earning rate is below \hat{r}_{ww}^1 , which is the greatest solution of the equation below:

$$\frac{9hr^{3/2}}{4} + 4b^{3/2}r + \left(\frac{9}{8}h^2 - \frac{9(1-a-b)}{4}h - 4b(1-a) \right) \sqrt{r} + \sqrt{b}(1-a)^2 = 0.$$

In particular, players with time cost $c < \hat{c}_{ww}^1$ will pay less, where:

$$\hat{c}_{ww}^1 = \frac{9h\sqrt{br}(1-a-b-r-h/2)}{4\left((1-a)^2 - 4\sqrt{br}(1-a-\sqrt{br})\right)}.$$

When $r < \hat{r}_1$ is feasible, there exist players who can pay less in virtual selling, compared to real selling, if

the earning rate is below \hat{r}_{ww}^2 , which is the greatest solution of the equation below:

$$\sqrt{br}^{3/2} - 3(1-a-b-h/3)\sqrt{br} + (1-a-h/2)(1-a-b) = 0.$$

In particular, players with time cost $c < \hat{c}_{ww}^2$ will pay less, where:

$$\hat{c}_{ww}^2 = \frac{\sqrt{br}(1-a-b-r-h/2)}{1-a-h/2-2\sqrt{br}}.$$

PROOF OF PROPOSITIONS 4

In real selling, when $\frac{\partial \tilde{p}_2^R}{\partial r} = -\frac{h}{2} < 0$, $\frac{\partial \tilde{p}_1^R}{\partial r} = -\frac{4}{9}(1-a-b-r) < 0$. Thus, the optimal price decreases in earning rate r .

In virtual selling, when $r \leq b$, the case degenerates to real selling and the optimal price decreases in r .

Thus, the optimal price decreases in r . When $b < r \leq \hat{r}_1$, we have $\frac{\partial \tilde{w}_2}{\partial r} = \sqrt{b/r}(a-h)/2$. Apparently,

$\frac{\partial \tilde{w}_2}{\partial r} > 0$ if $a > h$ and $\frac{\partial \tilde{w}_2}{\partial r} < 0$ if $a < h$. When $r > \hat{r}_1$ and $h \geq \hat{h}_3$, \tilde{w}_1 is the optimal price, and we have

$\frac{\partial \tilde{w}_1}{\partial r} = \sqrt{b/r}(16\sqrt{br} + 17a - 8)/18$. We can show that $\frac{\partial \tilde{w}_1}{\partial r} > 0$ if $r > \hat{r}_2 = \left(\frac{17a-8}{16\sqrt{b}}\right)^2$ and $\frac{\partial \tilde{w}_1}{\partial r} < 0$ if $r < \hat{r}_2$

. Compare the boundaries for r , we have: $\frac{\partial \tilde{w}_1}{\partial r} > 0$ if $r > \max(\hat{r}_1, \hat{r}_2)$ and $h \geq \hat{h}_3$. Combining these cases,

we find that when $h < \hat{h}_4 = \frac{3}{4}a$, two conditions are satisfied: (1) $\frac{\partial \tilde{w}_2}{\partial r} > 0$, as apparently, we have $a > h$,

and (2) $\frac{\partial \tilde{w}_1}{\partial r} > 0$, as we can show that $\hat{r}_1 \geq \hat{r}_2$ holds for all feasible a and $h \leq \hat{h}_3$.

Therefore, when $h < \hat{h}_4$, we have optimal price under virtual selling first decrease then increase in r , while the optimal price under real selling monotonic decrease in r .

PROOF OF PROPOSITION 5

Consider a set of high type players with ability to proceed a game equals λ_H so that all players will engage in the free game but not all of them will purchase the premium content, i.e., $1+b < \lambda_H < (1+b)/(1-a)$.

Consider another set of low type players with ability equals λ_L so that similar to the main base, some players with a high time cost will not adopt the game, i.e., $\frac{b+r}{1-a} < \lambda_L < 1+b$. Suppose low type consists d

of the market, and high type consists $(1-d)$ of the market.

First, consider a base case where ability is λ where $\frac{b+r}{1-a} < \lambda < \frac{1+b}{1-a}$. Following the logic of Propositions

1 and 2, we can solve for the optimal price and earning rate.

Specifically, we have players' decisions:

$$(1.1) \left\{ t_g^* = \frac{1}{\lambda} \left(\frac{w}{k} - a \right), g^* = 0, t^* = \frac{1}{\lambda} \frac{\lambda - c}{\lambda} \right\} \text{ if } \left\{ \frac{1-a-h}{\lambda} = \hat{c}_{3\lambda} < c \leq k\lambda, k \geq \hat{k}_B \right\},$$

$$(1.2) \left\{ t_g^* = \frac{1}{\lambda} \left(\frac{w}{k} - a \right), g^* = 0, t^* = \frac{a+h}{\lambda} \right\} \text{ if } \left\{ c \leq k\lambda, k < \hat{k}_B \right\} \text{ or } \left\{ c \leq \hat{c}_{3\lambda}, k \geq \hat{k}_B \right\},$$

$$(2.1) \left\{ t_g^* = 0, g^* = w - ak, t^* = \frac{1}{\lambda} \frac{\lambda - c}{\lambda} \right\} \text{ if } \left\{ c > k\lambda, k \geq \hat{k}_B \right\} \text{ or } \left\{ c > \hat{c}_{3\lambda}, k < \hat{k}_B \right\},$$

$$(2.2) \left\{ t_g^* = 0, g^* = w - ak, t^* = \frac{a+h}{\lambda} \right\} \text{ if } \left\{ k < c \leq \hat{c}_{3\lambda}, k < \hat{k}_B \right\}.$$

Following the same logic as the proof for Proposition 2, we can solve for the corresponding optimal choice of earning rate and equilibrium price, which is summarized below:

$$\text{i. When } r > b \text{ and } h \geq \hat{h}_{2\lambda}^b : \quad \tilde{k}_{1\lambda}^b = \sqrt{br}/\lambda, \quad \tilde{w}_{1\lambda}^b = \frac{2}{9} \left(1-a - 2\tilde{k}_{1\lambda}^b \right)^2 + a\tilde{k}_{1\lambda}^b;$$

$$\text{ii. When } r > b \text{ and } h < \hat{h}_{2\lambda}^b : \quad \tilde{k}_{2\lambda}^b = \sqrt{br}/\lambda, \quad \tilde{w}_{2\lambda}^b = \frac{h}{2} \left(1-a - \frac{h}{2} - 2\tilde{k}_{2\lambda}^b \right) + a\tilde{k}_{2\lambda}^b;$$

$$\text{iii. When } r \leq b \text{ and } h \geq \hat{h}_{1\lambda}^b : \quad \tilde{k}_{3\lambda}^b = b/\lambda, \quad \tilde{w}_{3\lambda}^b = \frac{2}{9} \left(1-a - \frac{b+r}{\lambda} \right)^2 + ab/\lambda;$$

iv. When $r \leq b$ and $h < \hat{h}_{1\lambda}$: $\tilde{k}_{4\lambda}^b = b/\lambda$, $\tilde{w}_{4\lambda}^b = \frac{h}{2} \left(1 - a - \frac{h}{2} - \frac{b+r}{\lambda} \right) + ab/\lambda$.

When two types of players exist in the market, we consider three cases: (1) both types have play-to-buy players, (2) only high type has play-to-buy players, (3) neither type have play-to-buy players. The realization of each group depends on the revenue rate r .

For ease of presentation, we use subscript H to refer to high type, and L to show the low type. Let

$u = d\lambda_L + (1-d)\lambda_H$ and $v = d\lambda_L^{-1} + (1-d)\lambda_H^{-1}$. To avoid trivial cases, we assume $h \leq \frac{2}{3} \left(1 - a - \frac{2b}{u} \right)$.

Case 1: Both types have play-to-buy players

Let π_H and π_L be the profit when market consists of high type players only and low type players only,

correspondingly. As the two types share the same segmentation pattern, which requires $r > \hat{r}_{2\lambda} = \frac{u}{\lambda_L^2} b$, we

have $\pi_1 = d\pi_L + (1-d)\pi_H$. We conduct the bivariate optimization by solving first order condition and

checking the Hessian matrix. The result can be expressed as below:

When $h > \hat{h}_{1\lambda} = \frac{2}{3} (1 - a - 2\tilde{k}_{1\lambda})$, the optimal choices are: $\tilde{k}_{1\lambda} = \sqrt{br} \sqrt{v/u}$, $\tilde{w}_{1\lambda} = \frac{2}{9} (1 - a - 2\tilde{k}_{1\lambda})^2 + a\tilde{k}_{1\lambda}$.

When $h \leq \hat{h}_{1\lambda}$, the optimal choices are: $\tilde{k}_{2\lambda} = \sqrt{br} \sqrt{v/u}$, $\tilde{w}_{2\lambda} = \frac{h}{2} \left(1 - a - \frac{h}{2} - 2\tilde{k}_{2\lambda} \right) + a\tilde{k}_{2\lambda}$.

Similar to Proposition 2, we conduct region transfer, and have results below:

When $r > \hat{r}_{1\lambda}$ which is valid if:

$$h > \hat{h}_{2\lambda} = \max \left\{ \frac{2}{3} \left(1 - a - 2\sqrt{(1-a-b)bv/u} \right), \frac{2}{3} \left(1 - a - 2\sqrt{(1-3b)bv/u} \right) \right\}:$$

$$\tilde{k}_{1\lambda} = \sqrt{br} \sqrt{v/u}, \quad \tilde{w}_{1\lambda} = \frac{2}{9} (1 - a - 2\tilde{k}_{1\lambda})^2 + a\tilde{k}_{1\lambda}$$

When $\hat{r}_{2\lambda} < r \leq \hat{r}_{1\lambda}$, the result is:

$$\tilde{k}_{2\lambda} = \sqrt{br} \sqrt{v/u}, \quad \tilde{w}_{2\lambda} = \frac{h}{2} \left(1 - a - \frac{h}{2} - 2\tilde{k}_{2\lambda} \right) + a\tilde{k}_{2\lambda}.$$

Notably, similar to Proposition 2, $\hat{r}_{1\lambda}$ is the solution of $f^{-1}(\hat{h}_{1\lambda})$, with $\hat{r}_{1\lambda} = \frac{(2-2a-3h)^2}{16b} \cdot \frac{u}{v}$.

Case 2: Only high type has play-to-buy players

As low type does not have play-to-buy players, we recalculate the profit function denoted as π_{L2} . Let

$\pi_2 = d\pi_L + (1-d)\pi_H$. Solving for first order condition and checking the result of Hessian matrix, we have:

when $h \leq \frac{2}{3}\left(1-a-\frac{2b}{u}\right)$, the equilibrium result would be:

$$\tilde{k}_{3\lambda} = \sqrt{\frac{br}{\lambda_H}}, \text{ and } \tilde{w}_{3\lambda} = \frac{h}{2}\left(1-a-\frac{h}{2}-\eta\right) + a\tilde{k}_{3\lambda}, \text{ where } \eta = \frac{d}{u}(b+r) + \frac{1-d}{u}(2\sqrt{br}).$$

Case 3: Neither type has play-to-buy players

When neither type has play-to-buy players, the case degenerates to the real selling case as nobody would purchase through playtime, and the firm will choose the lowest earning rate possible. We solve the optimization problem and find that under feasible regions, the results are:

$$\tilde{k}_{4\lambda} = b/\lambda_H, \text{ and } \tilde{w}_{4\lambda} = \frac{h}{2}\left(1-a-\frac{h}{2}-\frac{b+r}{u}\right) + a\tilde{k}_{4\lambda}$$

Below we summarize the firm's optimal choice of earning rate and price, and the corresponding profit.

Case	Time revenue rate	Equilibrium earning rate, module price, and the corresponding provider's profit
1	High ($r > \hat{r}_{1\lambda}$)	$\tilde{k}_{1\lambda} = \sqrt{v/u}\sqrt{br}, \tilde{w}_{1\lambda} = \frac{2}{9}(1-a-2\tilde{k}_{1\lambda})^2 + a\tilde{k}_{1\lambda},$ $\tilde{\pi}_{1\lambda} = \frac{2u}{27(1+r)}(1-a-2\tilde{k}_{1\lambda})^3 + const_H$
2	Medium High ($\hat{r}_{2\lambda} < r \leq \hat{r}_{1\lambda}$)	$\tilde{k}_{2\lambda} = \sqrt{v/u}\sqrt{br}, \tilde{w}_{2\lambda} = \frac{h}{2}\left(1-a-\frac{h}{2}-2\tilde{k}_{2\lambda}\right) + a\tilde{k}_{2\lambda}$ $\tilde{\pi}_{2\lambda} = \frac{uh}{4(1+r)}\left(1-a-\frac{h}{2}-2\tilde{k}_{2\lambda}\right)^2 + const_H$

3

Medium Low

$$(b < r \leq \hat{r}_{2\lambda})$$

$$\tilde{k}_{3\lambda} = \sqrt{br}/\lambda_H, \quad \tilde{w}_{3\lambda} = \frac{h}{2} \left(1 - a - \frac{h}{2} - \eta \right) + a\tilde{k}_{3\lambda}$$

$$\tilde{\pi}_{3\lambda} = \frac{uh}{4(1+r)} \left(1 - a - \frac{h}{2} - \eta \right)^2 + \text{const}_L$$

4

Low

$$(r \leq b)$$

$$\tilde{k}_{4\lambda} = b/\lambda_H, \quad \tilde{w}_{4\lambda} = \frac{h}{2} \left(1 - a - \frac{h}{2} - \frac{b+r}{u} \right) + ab/\lambda_H,$$

$$\tilde{\pi}_{4\lambda} = \frac{uh}{4(1+r)} \left(1 - a - \frac{h}{2} - \frac{b+r}{u} \right)^2 + \text{const}_L$$

where $\hat{r}_{1\lambda} = \frac{(2-2a-3h)^2}{16b} \cdot \frac{u}{v}$, $\eta = \frac{d}{u}(b+r) + \frac{1-d}{u}(2\sqrt{br})$, $\hat{r}_{2\lambda} = \frac{u}{\lambda_L^2 v} b$,

$$\text{const}_H = (r/2(1+r)) \left[(a+h)(1-a-h-vb) - (1-(1+b)/\lambda_H)^2 (1-d) \right] \text{ and}$$

$$\text{const}_L = \text{const}_H - (r/2(1+r)) (1-(1+b)/\lambda_L)^2 d.$$

PROOF OF COROLLARY 2

We take partial derivative of earning rate w.r.t. d directly, and have:

$$\frac{\partial \tilde{k}_{1\lambda}}{\partial d} = \frac{\partial \tilde{k}_{2\lambda}}{\partial d} = \frac{(\lambda_H - \lambda_L)(\lambda_H + \lambda_L)}{\lambda_H \lambda_L u^2} \sqrt{br} > 0.$$

Note that d is the portion of low-skill group. Thus, the equilibrium earning rate decrease in the share of high-skill group.

PROOF OF COROLLARY 3

The proof for profit comparison, social welfare comparison and the influence of revenue rate on optimal price follow the same idea of Proposition 3 and 4, correspondingly. Below we provide more details.

Profit Comparison

The optimal profit, regardless of the selling strategy, can be expressed as:

$$\pi_1 = \frac{2u}{27(1+r)}(1-a-x)^3 + \text{const} \text{ when } h > \hat{h}, \text{ and}$$

$$\pi_2 = \frac{uh}{4(1+r)}\left(1-a-\frac{1}{2}h-x\right)^2 + \text{const} \text{ when } h < \hat{h}.$$

Let $\pi_{iH}^V, \pi_{iM}^V, \pi_{iL}^V$ be the optimal profit for virtual selling where $r > \hat{r}_1, b < r \leq \hat{r}_1, r \leq b$, respectively, where $i \in \{1, 2\}$. Let π_i^R be the optimal price for real selling, where $i \in \{1, 2\}$. Thus, let $\hat{h}_H^V, \hat{h}_M^V, \hat{h}_L^V, \hat{h}^R$ be the margin of h for virtual selling $r > \hat{r}_1, b < r \leq \hat{r}_1, r \leq b$ and real selling, respectively.

const refers to a ‘‘constant term’’ that is not influenced by the profit optimization procedure. Real selling and virtual selling with $r \leq \hat{r}_1$ share the same *const* (also the same across π_1 and π_2), denoted as const_L . When $r > \hat{r}_1$, π_1 and π_2 share another constant term, denoted as const_H . We know $\text{const}_H > \text{const}_L$.

First, we find that $\pi_1^R = \pi_{1L}^V$, $\pi_2^R = \pi_{2L}^V$ and $\tilde{h}_L^V = \tilde{h}^R$. This is consistent with the base case, where virtual selling degenerates to real selling. When $r > b$, we know that $\hat{h}_H^V > \hat{h}^R$ and $\hat{h}_M^V > \hat{h}^R$. Consider the following cases:

- i. Compare π_{1H}^V with π_1^R when $h > \hat{h}_H^V$;
- ii. Compare π_{1M}^V with π_1^R when $h > \hat{h}_M^V$;
- iii. Compare π_{2H}^V with π_2^R when $h < \hat{h}^R$;
- iv. Compare π_{2M}^V with π_2^R when $h < \hat{h}^R$;

v. Compare π_1^R with π_{2H}^V when $\hat{h}^R \leq h \leq \hat{h}_H^V$;

vi. Compare π_1^R with π_{2M}^V when $\hat{h}^R \leq h \leq \hat{h}_M^V$.

For Cases i to iv, we know that $\frac{\partial \pi_1}{\partial x} < 0$ and $\frac{\partial \pi_2}{\partial x} < 0$. In real selling, $x = x_b \triangleq \frac{b+r}{u}$. In virtual selling,

$$x = \begin{cases} x_b & r \leq b \\ \eta & b < r \leq \hat{r}_1 \\ 2\hat{k}_{1\lambda} & r > \hat{r}_1 \end{cases}$$

We know that $\eta > x_b$ and $2\hat{k}_{1\lambda} > x_b$. Thus, we have: $\pi_{iH}^V > \pi_i^R$ and $\pi_{iM}^V > \pi_i^R$ in the corresponding feasible region, where $i \in \{1, 2\}$.

For Cases v and vi, let $\hat{\pi} = \pi - const$. We check the sensitivity of optimal profit on h and find that $\frac{\partial \hat{\pi}_1}{\partial h} = 0$

, and $\frac{\partial \hat{\pi}_2}{\partial h} > 0$. Therefore, $\hat{\pi}_1|_{h=\hat{h}^R} = \hat{\pi}_1|_{h=\hat{h}_M^V} = \hat{\pi}_1|_{h=\hat{h}_H^V}$, while $\hat{\pi}_2|_{h=\hat{h}^R} < \hat{\pi}_2|_{h=\hat{h}_M^V}$ and $\hat{\pi}_2|_{h=\hat{h}^R} < \hat{\pi}_2|_{h=\hat{h}_H^V}$. Recall

that when $h < \hat{h}^R$, we have $\hat{\pi}_{2H}^V > \hat{\pi}_2^R$ and $\hat{\pi}_{2M}^V > \hat{\pi}_2^R$. Thus, we have:

$$\hat{\pi}_{2M}^V|_{\hat{h}^R < h < \hat{h}_M^V} > \hat{\pi}_{2M}^V|_{h=\hat{h}^R} > \hat{\pi}_2^R|_{h=\hat{h}^R} = \hat{\pi}_1^R|_{h=\hat{h}^R} = \hat{\pi}_1^R|_{\hat{h}^R < h < \hat{h}_M^V}, \text{ i.e., } \hat{\pi}_{2M}^V|_{\hat{h}^R < h < \hat{h}_M^V} > \hat{\pi}_1^R|_{\hat{h}^R < h < \hat{h}_M^V} \text{ and}$$

$$\hat{\pi}_{2H}^V|_{\hat{h}^R < h < \hat{h}_H^V} > \hat{\pi}_{2H}^V|_{h=\hat{h}^R} > \hat{\pi}_2^R|_{h=\hat{h}^R} = \hat{\pi}_1^R|_{h=\hat{h}^R} = \hat{\pi}_1^R|_{\hat{h}^R < h < \hat{h}_H^V}, \text{ i.e., } \hat{\pi}_{2H}^V|_{\hat{h}^R < h < \hat{h}_H^V} > \hat{\pi}_1^R|_{\hat{h}^R < h < \hat{h}_H^V}.$$

Note that when $b < r \leq \hat{r}_1$, the constant term for virtual selling and real selling is the same, thus, we have:

$$\pi_{2M}^V = \hat{\pi}_{2M}^V + const_L > \hat{\pi}_1^R + const_L = \pi_1^R \text{ when } \hat{h}^R < h < \hat{h}_M^V.$$

When $r > \hat{r}_1$, the constant term for virtual selling dominates that for real selling. Thus, we have:

$$\pi_{1M}^V = \hat{\pi}_{1M}^V + const_H > \hat{\pi}_{1M}^V + const_L > \hat{\pi}_1^R + const_L = \pi_1^R \text{ when } \hat{h}^R < h < \hat{h}_H^V.$$

Thus, we find that the profit under virtual selling weakly dominates that under real selling.

Consumer Surplus Comparison

Similar to profit comparison, we know that the consumer surplus under virtual and real selling are equivalent to each other when $r \leq b$ due to degeneration. When $r > b$, we consider 6 cases below:

- i. Compare CS_{2H}^V with CS_2^R when $h < \hat{h}^R$;
- ii. Compare CS_{2M}^V with CS_2^R when $h < \hat{h}^R$;
- iii. Compare CS_{1H}^V with CS_1^R when $h > \hat{h}_H^V$;
- iv. Compare CS_{1M}^V with CS_1^R when $h > \hat{h}_M^V$;
- v. Compare CS_1^R with CS_{2H}^V when $\hat{h}^R \leq h \leq \hat{h}_H^V$;
- vi. Compare CS_1^R with CS_{2M}^V when $\hat{h}^R \leq h \leq \hat{h}_M^V$.

Cases i and ii share the same pattern. Let $\Delta CS = CS_2^R - CS_2^V$, which decreases in $(2a + h)$. When $(2a + h)$ reaches the maximum value, we can show that $\Delta CS > 0$ under the feasible region for λ_H and λ_L . Thus, we have $CS_2^R > CS_{2M}^R$ and $CS_2^R > CS_{2H}^R$ when $h < \hat{h}^R$.

Cases iii and iv share the same pattern. We have $\frac{\partial^2 \Delta CS}{\partial a^2} < 0$, $\frac{\partial \Delta CS}{\partial a} < 0$, $\frac{\partial \Delta CS}{\partial h} = 0$. When a reaches its maximum value at $a = \min\{1 - b - r, 1 - 2b\}$, we can show that $\Delta CS > 0$ for all feasible λ_H and λ_L . Thus, we have $CS_1^R > CS_{1M}^V$ and $CS_1^R > CS_{1H}^V$ when $h > \hat{h}_M^V$ and $h > \hat{h}_H^V$, correspondingly.

Cases v and vi follows the same logic as the proof of profit comparison. We know that $\frac{\partial CS_1}{\partial h} = 0$ and $\frac{\partial CS_2}{\partial h} > 0$. Note that case iii and iv shows that $CS_1^R > CS_1^V$ under the corresponding region. Note also that

the consumer surplus is continuous: $CS_{1i} = CS_{2i}$ when $h = \hat{h}_i^V$ for $i \in \{M, H\}$. Thus, for $i \in \{M, H\}$:

$$CS_1^R \Big|_{\hat{h}^R \leq h \leq \hat{h}_i^V} = CS_1^R \Big|_{h = \hat{h}_i^V} = CS_1^R \Big|_{h > \hat{h}_i^V} > CS_1^V \Big|_{h > \hat{h}_i^V} = CS_{2i}^V \Big|_{h = \hat{h}_i^V} > CS_{2i}^V \Big|_{\hat{h}^R \leq h \leq \hat{h}_i^V}.$$

Combining all cases, we know that the consumer surplus under virtual selling is lower than that under real selling when $r > b$. The consumer surplus under the two strategies are the same when $r \leq b$.

Influence of earning rate

In real selling, when $\frac{\partial \tilde{p}_{2\lambda}^R}{\partial r} = -\frac{h}{2u} < 0$, $\frac{\partial \tilde{p}_1^R}{\partial r} = -\frac{4}{9}\left(1 - a - \frac{b+r}{u}\right) < 0$. Thus, the optimal price decreases in earning rate r .

In virtual selling, when $r \leq b$, the case degenerates to real selling and the optimal price decreases in r . Thus, the optimal price decreases in r .

When $b < r \leq \hat{r}_{2\lambda}$, we have $\frac{\partial \tilde{w}_{3\lambda}}{\partial r} = \frac{a}{2\lambda_H} \sqrt{b/r} - \left(d + \sqrt{b/r}(1-d)\right) \frac{h}{2u} > 0$ under the feasible region.

When $\hat{r}_{2\lambda} < r \leq \hat{r}_{1\lambda}$, and when $r > \hat{r}_{1\lambda}$ and $\tilde{w}_{1\lambda}$ is the optimal price, the influence of r is the same as the base case. Specifically, we have $\frac{\partial \tilde{w}_{2\lambda}}{\partial r} = \sqrt{vb/(ur)}(a-h)/2$. Thus, $\frac{\partial \tilde{w}_{2\lambda}}{\partial r} > 0$ if $a > h$. We also have

$\frac{\partial \tilde{w}_1}{\partial r} = \frac{\sqrt{vb/r}}{18u} (16\sqrt{br} + \sqrt{u}(17a-8))$. We can show that $\frac{\partial \tilde{w}_1}{\partial r} > 0$ if $r > \hat{r}_{3\lambda} = \left(\frac{(17a-8)\sqrt{u}}{16\sqrt{b}}\right)^2$, and

$\hat{r}_{1\lambda} \geq \hat{r}_{3\lambda}$ holds for all feasible a and h such that $\tilde{w}_{1\lambda}$ can be reached.

Combining all cases, we know that the optimal price first decrease then increase in the revenue rate as long

as the continuation value h satisfies $h < \hat{h}_{4\lambda} = \min\left\{\frac{3}{4}a, \frac{2}{3}\left(1 - a - \frac{2b}{u}\right)\right\}$.

VITA

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