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Satiation and cross promotion: Selling and swapping users in mobile games ☆

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ABSTRACT

One of the main challenges facing the mobile game industry is an alarming level of satiation, that is, a decline in user engagement and consequently in ad viewing, spending, and retention. Satiation lowers users' CLV to an extent that renders acquisition from the likes of Facebook and Google untenable, driving game publishers to cross-promote, that is, sell and swap users among themselves. We model this cross-promotion as first, a ***screening mechanism***, in that the fact of playing a game indicates specific preferences that might be suitable to an exchange with similar games; and second, as a ***resetting mechanism*** that enables the swapped users to reset their engagement in the new game, thus rendering the swap or sell beneficial to both buyer and seller. We show that there exists an optimal level of satiation with a game, and with this level, we show the conditions under which the game publisher cross promotes, and when it does, what the conditions are for selling rather than swapping. We extend the analysis to the case in which advertising costs and conversion rates are related; explain why they might be negatively correlated, and show that our main results still hold.

1. Introduction

Consumers increasingly turn their attention to online hedonic experiences such as music streaming, mobile games, and YouTube videos, consistent with the trend of focusing on experiences rather than goods (Morgan 2019). These hedonic experiences often suffer from the effect of satiation, where the repeated consumption of the same experience produces a decline in use (Galak and Redden 2018), in turn leading to a decline in use-related revenues such as advertising or in-app purchases. This in turn results in low customer lifetime value (CLV), which often renders acquisition costs through channels such as Facebook or Google untenable.

In a scenario wherein customer value declines over time, there can be a point at which the customer's value can be higher for a third party, particularly in a new experience where s/he is not yet satiated. This can make the idea of "selling" the customer an appealing option. While a customer cannot easily be sold like any other asset, firms can incentivize proactive churn

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by giving existing customers access to the offers of competing firms. Such proactive churn management is particularly prevalent in a major area of hedonic consumption experience: the mobile games industry. Here, firms often sell advertising slots to competitors, who use them to advertise their products (Han et al., 2016; Appel et al., 2020). The focal firm engages in such behavior, knowing it may result in the churn of some existing customers. We use the mobile game industry's nomenclature to label this type of proactive churn ***cross-promotion***.[1]

To better understand cross-promotion, we examined mobile game industry publications and research reports, followed presentations at industry conventions, and interviewed executives at global gaming publishers and ad networks. In doing so, we identified a unique combination of motivations and abilities that renders the mobile gaming industry a forerunner of new models of customer management in an increasingly data-driven digital world. In particular, we observe the following four characteristics of these markets:

- **First, an ecosystem characterized by intense cash-flow pressure:** Many casual mobile games begin as free and have high customer acquisition costs, resulting in low CLV. To survive the cash-flow pressure, game publishers have developed an ability to manage users on an individual level that is more advanced than in most other markets. This ability draws on an ecosystem that includes a) external sources of customer acquisition such as Facebook and Google that enable smart customer acquisition based on customer knowledge, b) data science-based ad networks that mediate between advertisers and app publishers, and c) app publishers who can follow time-sensitive user behavior in depth and continuously communicate with them.
- **Second, the ubiquity of cross-promotion:** We observe the prevalence of cross-promoting customers to increase profits, particularly in casual and hyper-casual games where monetization is built around advertising. As reported by Luz (2019), "*Currently, the majority of those advertising in-game are other games*." Indeed, a senior manager for a sizeable hyper-casual game publisher told us in an interview, "*To a large extent, much of our efforts are about buying and selling customers*." An executive in a major global ad network estimated that most games he deals with publish click-through advertising to other (competing) games, in many cases leading to churn. Market reports that assess customer churn from ads from various sources advise publishers to analyze the effect of churn on CLV in order to decide on their advertising policy (Lerner 2019).
- **Third, the selling and buying of users within the same publisher portfolio:** The pricing mechanism that enables selling and buying users is also used when selling occurs within games of the same publisher. The reason is that games are managed by brand managers who are reluctant to give a customer away to another game of the same publisher unless compensated by a reasonable price. Our interviews suggest that while app publishers may be aware of the possibility of churn via ads from other apps, they do not necessarily analyze the total effect on customer value, thus some are reluctant to use cross-promotion.
- **Fourth, the emergence of blacklisting:** A common practice in the mobile gaming industry is blacklisting, i.e., preventing the promotion of specific apps or apps belonging to certain categories (Kim 2020, Digital Limbo 2019). As cross-promotion may involve swapping customers, blacklisting a firm affects the type of customers it transfers and the ones it can obtain. There is discussion and some criticism among industry observers of the utility of blacklisting, and the question of its net effect is still open.

The objective of our analysis is to provide a better understanding of the cross-promotion phenomenon by examining, via a formal model, the market conditions that lead to cross-promotion in which brands sell their customer to other brands. We consider a game publisher faced with the decision of whether to acquire a given customer. The game publisher can acquire customers from *outside market* sources such as Facebook and Google, trading the customer acquisition cost (*CAC*) in exchange for the expected *CLV* of the customer. What cross-promotion brings into the picture are the possibilities in an *inside market*, i.e., cooperating with another game. Such cooperation can occur by placing a click-through ad in another game and then paying per installed user or swapping customers and "paying" with one of their customers. This cross-promotion is, first, a ***screening mechanism*** in that the fact of playing a game indicates specific preferences that bode well for an exchange with similar games; and second, a ***resetting mechanism*** that allows the swapped users to reset their engagement in the new game, that is, the customer is transferred, and their low engagement is reset to a higher level with the new experience, thus rendering the swap beneficial to both buyer and seller.

The equilibrium resulting from this complex ecosystem enables us to understand the conditions under which selling and swapping customers emerge. Specifically, we obtain the following four findings: First, we show that in equilibrium, the game publisher cross promotes when the quality of the inside market is above a given threshold, regardless of the quality of the outside market. The outside market only comes into play when deciding whether to swap or purchase from a rival. Second, we show that in equilibrium, the likelihood of cross-promotion (either selling to or swapping a user from a rival) increases in satiation and decreases in retention. It also decreases in gross profits and increases in the costs of designing a game. Third, we show that in equilibrium, given that the firm has decided to cross-promote, the likelihood of observing swapping decreases with gross profits and retention; and increases with the cost of designing a game. Finally, our analysis helps explain why

[1] There are two common usages of the term "cross-promotion": The act of advertising in a competitor's game (Lee et al. 2020), and the resultant transfer of a user from one competitor to the other via swapping or selling. We use both, as the context unambiguously indicates the meaning of the term.

blacklisting, a common tactic in the mobile game industry that prevents the cross-promotion of specific apps, will increase the likelihood of cross-promotion (either purchasing or swapping a user from a rival). We extend our analysis to the case in which advertising costs and conversion rates are related; explain why they might be negatively correlated; and show that our results still hold.

Our framework and findings can be of interest beyond the (sizeable) market for mobile games. An example is the market for personalized content recommendations in online news outlets (Song, Sahoo, and Ofek 2018). Like mobile games, online news outlets suffer from user satiation, and actively redirect customers to other media outlets via recommendation platforms. The technological capability of sophisticated intermediaries such as Taboola and Outbrain to conduct data-based analysis and increase profitability for all parties is pivotal in this market. In an interview, the CEO of one of these two firms noted the extreme difficulties he faced when the firm was a startup, convincing commercial websites to send customers away to competitors; and the need to convince other players about satiation and the benefit of transferring customers. As selling customers may become relevant wherever customer satiation and the ability to manage customers intersect, an in-depth analysis of these intriguing markets can be of great interest.

2. Background

Our research addresses research avenues of customer satiation, customer profitability, recommendation mechanisms, and mobile app monetization.

Customer Satiation: Satiation describes a situation in which users grow tired of repeatedly experienced stimuli, and reduce consumption even when satisfied with the product. Satiation has crucial implications for managing customers: The level of satiation and the resulting customer variety-seeking behavior has been shown to impact a firm's marketing strategy, such as the types of products carried, the monetization mechanisms used, and the design and pricing strategies applied (Appel et al. 2020; Caro and Martínez-de-Albéniz 2012; Sajeesh and Raju 2010). A rich behavioral literature has emerged in recent years identifying ways to mitigate hedonic satiation (Galak and Redden 2018; Lasaleta and Redden 2018; Sevilla et al. 2016). For example, firms may want to create breaks in consumption, such as commercial clips; change the consumption rate; or encourage consumers to anticipate future variety (Galak et al., 2013; Nelson et al., 2009; Sevilla et al. 2016). Cross-promotion is a different approach to mitigate the effects of satiation: Instead of changing the behavior of a given customer, the customer is transferred, and their low engagement is reset to a higher level with the new hedonic experience.

Customer Profitability: Our work is consistent with the view of customers as assets to be managed, which constitutes the base of the CRM literature (Gupta and Lehmann 2003; Rust, Lemon, and Zeithaml 2004). Work in this area has examined issues such as the importance of managing a customer portfolio (Johnson and Selnes 2004); the interaction with other assets of the firm (Fang, Palmatier, and Grewal 2011); and the use of customer acquisition, retention, and development to manage the customer asset (Bolton, Lemon, and Verhoef 2004; Lewis 2006). In the CRM literature, it is accepted that the expected profitability of customers should be considered in investment and customer acquisition decisions (Peters, Verhoef, and Krafft 2015) and that the mode of acquisition (e.g., discounts, word of mouth) can affect the consequent CLV (Lewis 2006; Villanueva, Yoo, and Hanssens 2008). We add to this impressive literature the idea of the firm's ability to profit from the asset by proactive churn, which should also be considered in resource allocation for customer acquisition.

Recommendation Mechanisms: Cross-promotion is, in many cases, initiated through an advertisement for a competing product or service. This advertisement is *de facto* a recommendation of the firm to try another product. Firms can recommend products to customers in various ways, the best known of which is *cross-selling* (Knott et al. 2002; Li et al. 2011; Prins and Verhoef 2007; Schmitz et al. 2014). In the digital world, cross-selling can be done via recommendation systems that suggest products based on similarity to the consumption of other customers (Oestreicher-Singer et al. 2013); and by enabling sellers to send links to other sellers in social commerce networks (Dellarocas et al. 2013; Stephen and Toubia 2010). One issue that distinguishes cross-promotion from other recommendation mechanisms is the need to directly consider the loss of customer lifetime value when the customer is transferred.

Mobile App Monetization: Finally, our work joins an emerging literature addressing mobile app monetization. Much attention has been given to the app publisher's tradeoff and the need to balance revenues between free and paid app versions. Recent efforts in this domain have focused on the issues of pricing and design (Cao, Chintagunta, and Li 2021), satiation (Appel et al. 2020), network effects (Shi, Zhang, and Srinivasan 2019), and longer-term customer retention (Ascarza, Netzer, and Runge 2020). Our work addresses the challenges of app monetization from another angle: the terms under which app publishers will use cross-promotion, further monetizing customers.

3. Cross promotion in mobile games

Mobile Game Environment: Mobile games are the most popular form of gaming, are growing fast, and are by far the largest app category. The market for mobile games was estimated at more than $40b in the first half of 2021, and represents more than half of all App Store and Google Play app revenues (SensorTower 2021) combined. It is also estimated that more than 2.5 billion people worldwide, heterogeneous in age and with balanced gender representation, play mobile games (Silver

2020(. The mobile game industry is a vibrant echo system with continually emerging new business models for profit creation (Choi et al., 2020).

One can divide mobile games into three broad types: C*ore games* (e.g., Clash of Clans) are often targeted at specific niches and generally require players to invest significant time to learn. As a result, core games have the highest engagement among games. *Casual games* (e.g., Candy Crush) have more mass-market appeal. They typically have more straightforward game mechanics and rules and can be picked up quickly. *Hyper-casual games* (e.g., 2048) are even simpler to learn. They are instantly playable with little learning time, require scant attention, and have intuitive mechanics consistent throughout gameplay (Karnes 2021). Hyper-casual games are the most significant type in terms of number of downloads (but not revenues) (AppsFlyer 2022).

In terms of monetization, more than 90 % of mobile games start for free (free-to-play), relying mainly on two mechanisms of monetization: in-app purchases, and advertising (Appel et al. 2020). In-app purchases are the source of most revenue, particularly for core and casual games. However, the contribution of advertising has increased significantly in recent years, and hyper-casual games are primarily monetized by advertising (Frid 2019).

Motivating Evidence of Cross Promotion: To motivate our investigation, we present model-free evidence from an established publisher of multiple mobile games, several of which have reached the Top 100 in the major app stores. We obtained data on the adoption, retention, and usage of nine consecutive games, where each game was introduced one week after the launch of the previous one. This example represents a case of *internal cross-promotion*, where a customer is transferred to another product within the publisher's portfolio. Game publishers create a portfolio of products to ensure that the satiated customers of one game will become the new customers of another of their games (Popescu 2020). Large game publishers like Disney use this strategy in mobile games (Wong 2016).

The similarity to external cross-promotion occurs because brand managers in such multi-game companies frequently act independently and choose whether to use internal cross-promotion or acquire users from an outside source. The cross-promotion process is outsourced to an advertising network that uses its data science capabilities to find the right candidate, similar to finding an outside partner (e.g., IronSource 2021). In such cases, while the game publisher that owns the portfolio profits by being both the seller and the buyer, the buyer and seller can maximize their independent profits in such a way as to resemble the analysis that is our focus here. We provide further analysis in Section 6 for cases where the games are not set up as independent profit centers.

The Fast Decline of Active Users: Fig. 1 depicts the number of active users of one casual game (Game 3). Consistent with industry reports on casual games, we see a fast decline where only about a quarter of players are active after two months (eight weeks). This fast decline can be explained by the difficulty in retaining users who did not pay (Datta, Foubert, and Van Heerde 2015), and the satiation that characterizes most mobile games (Han et al. 2016; Hui 2017).

The Extent of Cross Promotion: Table 1 shows the extent of cross-promotion across nine games. We see, for example, that 10 % of the users of Game 10 came from Game 9; an additional 4.5 % came from Game 8; and a total of 22.7 % of all Game 10 users came from cross-promotion. Looking only at games with at least four previous games feeding into them (Games 5 and above), we see that cross-promotion effect size systematically exceeds 20 %, with an average of 28.6 % for Games 5 to 10. Therefore, more than a quarter of each game's user base stems from cross-promotion, which shows the overall considerable size of the phenomenon.

Retention, Satiation, and Cross Promotion: Table 2 shows a typical dataset for one of the games (Game 3), including the total number of play sessions and average session length per week for each game. This enables us to determine the total activity (number of sessions times average session length). By dividing this measure by the number of active users, we compute the average activity per active user in the last column of the table. This last column clearly shows a decline in activity per user over time that reflects satiation.

To show the relationship between satiation and cross-promotion, we ran a log-linear regression for each game where the activity per user at time t is given by.

$\text{Activity per user}_t = \text{Baseline activity} \cdot \delta^t$, where δ is a parameter that captures the extent of satiation. Similarly, we can measure retention for each game: We look at the evolution of the number of total active users for each game, and following a log-linear regression, similar to the one we use for satiation; and we thus compute the average retention rate for each app. Table 3 presents the cross-promotion size, estimated satiation, and average retention for each of the nine games.

The correlation between cross-promotion size and the satiation parameter is substantial and significant (-0.65). Therefore, the lower the satiation parameter, i.e., the higher the satiation (as low δ implies high satiation), the greater the size of the cross-promotion effect. We also see that the correlation between cross-promotion size and retention rate is substantial and significant (-70 %). Accordingly, the lower the retention rate, the larger the size of the cross-promotion effect.

Beyond this specific example, the question is whether the relationship between cross-promotion, satiation, and retention can be generalized. To understand that, one needs to conduct a comprehensive analysis that considers the interests of the buyers and sellers of the inside market and the outside market alternative they have. In the following section, we show that these relationships emerge as a generalization of the market conditions that drive cross-promotion.

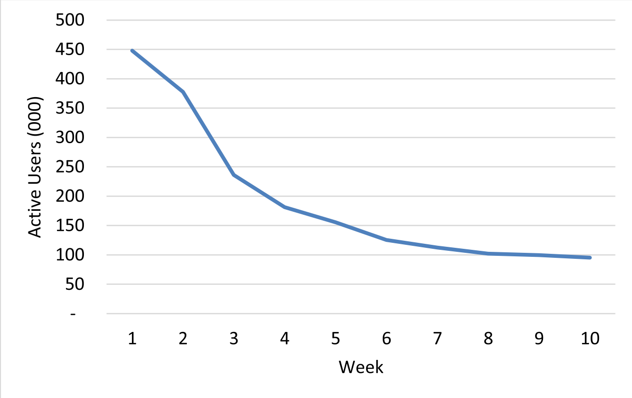

Fig. 1. Active Users of a Casual Mobile Game (000)* (*To preserve confidentiality, the numbers of active users are multiplied by a constant $1 \le \theta \le 1.3$).

Table 1
Cross-Promotion Size across Nine Causal Mobile Games*.

		Feeding Game										
		Game 10	**Game 9**	**Game 8**	**Game 7**	**Game 6**	**Game 5**	**Game 4**	**Game 3**	**Game 2**	**Game 1**	**Total Cross Promoted**
Receiving Game	**Game 10**	–	10.0 %	4.5 %	2.1 %	1.3 %	1.0 %	0.8 %	0.5 %	1.8 %	0.7 %	**22.7 %**
	Game 9		–	14.9 %	4.8 %	3.5 %	1.1 %	0.9 %	0.8 %	3.2 %	1.4 %	**30.6 %**
	Game 8			–	15.0 %	8.3 %	3.3 %	2.0 %	1.8 %	2.8 %	3.6 %	**36.8 %**
	Game 7				–	10.0 %	4.8 %	2.0 %	1.7 %	2.4 %	4.1 %	**25.0 %**
	Game 6					–	12.7 %	5.8 %	3.6 %	3.4 %	4.6 %	**30.1 %**
	Game 5						–	14.0 %	4.6 %	4.2 %	3.5 %	**26.3 %**
	Game 4							–	7.4 %	5.1 %	2.9 %	**15.4 %**
	Game 3								–	15.9 %	2.6 %	**18.5 %**
	Game 2									–	0.9 %	**0.9 %**
	Game 1										–	**0.0 %**

* For example, 10% of Game 10 users came from Game 9, and an additional 4.5% came from Game 8.

Table 2
A Dataset Example (Game 3)*.

Week	Total Acquisitions (000)	Total Active (000)	Number of Sessions (000)	Session Length (minutes)	Activity per User (minutes)
1	447	448	1,653	7.2	26.7
2	185	378	1,681	6.1	27.2
3	56	236	900	5.4	20.7
4	33	181	635	5.1	18.0
5	25	155	510	5.3	17.4
6	16	126	409	5.2	17.0
7	13	112	353	5.4	16.8
8	10	102	318	5.2	16.2
9	13	100	308	5.2	16.1
10	13	95	305	5.7	18.1

* To preserve confidentiality, the numbers of active users are multiplied by a constant $1 \le \theta \le 1.3$.

4. Modelling cross-promotion

We analyze a game-theoretic setting with two market players: a buyer, and a seller, both game publishers. Each game publisher has one customer, and the buyer wants to acquire an additional customer. The seller is a game publisher willing to transfer such a customer to the buyer if approached, and if the price offered is worthwhile. The strategy space includes three options for each player: For the buyer, the strategies are to acquire the customer from the likes of Facebook; purchase the customer from the seller; or swap customers. The sellers' strategies are to keep the customer, sell the customer to the buyer, or swap customers. The result is a standard Nash Equilibrium, where each outcome is the preferred option for both players. A summary of the parameters used in the analysis is given in Table 4.

Table 3
Cross-promotion and Satiation*.

Game	Cross-promotion (from Table 1)	Satiation (δ)	Retention
Game 10	23 %	90 %	65 %
Game 9	31 %	94 %	76 %
Game 8	37 %	92 %	72 %
Game 7	25 %	94 %	76 %
Game 6	30 %	92 %	79 %
Game 5	26 %	94 %	79 %
Game 4	14 %	95 %	89 %
Game 3	19 %	95 %	84 %
Game 2	1 %	96 %	90 %
Correlation with cross-promotion		**−65 %**	**−70 %**

* As low δ implies high satiation, cross-promotion positively correlates with satiation.

Table 4
Model Parameters*.

Parameter	Description	Remarks
Exogenous Parameters		
α	Inside market conversion rate	$0 \leq \alpha \leq 1$
β	Outside market conversion rate**	$0 \leq \beta \leq 1$
r	Retention probability per period of current customer	$0 \leq r \leq 1$
g	Gross profit margins per period of current customer	
c	Cost parameter of designing a game	
CAC	Customer acquisition cost from the outside market**	
Endogenous Constructs/Parameters		
δ	Decline in gross profit margins per period due to satiation***	$0 \leq \delta \leq 1$
μ	Decline in retention probability per period due to satiation***	$0 \leq \mu \leq 1$
T	Time at which the buyer seeks a new customer	$1 \leq T$
PAC	Purchase acquisition costs from the inside market	
CLV	Expected lifetime value of a current customer at Time 1	
RSV	Expected residual lifetime value of a current customer at time T	

* An additional parameter is the discount rate d, which plays no role in mobile games, where the average stay is measured in weeks. For completeness' sake, we include it, yet disregard it in all sensitivity analyses.
** In Section 6, we address the case wherein *CAC* and the outside market conversion rate are related.
*** Low δ and μ imply high satiation.

Conversion Rates and Market Quality: One of the major drivers of our analysis is the tension between the acquisition of a user from external sources such as Google or Facebook, and buying (or swapping) a customer in the inside market from a competitor. We denote the conversion rates from these two markets as β and α respectively. Yet, they denote more than conversion rates: In a sense, these are the respective qualities of the two markets, as they measure the markets' ability to target advertising to prospective users that fit the game well.

In Section 6, we discuss the case where the resetting of engagement is incomplete. For example, in Game 3 in Table 2, the activity per user begins at about 27 min per day in Week 1, and declines to 16 min in Week 8. Suppose the customer is reset this week. We assume that the resetting is complete, i.e., the customer starts playing the new game at 27 min per day. In some setting, we can expect some level of satiation across games, instead of a full reset. Instead of resetting to the full 27 min, the player in our example above might, for example, reset to only 25 min. This incomplete reset will be reflected in the new conversion parameter that considers both phenomena. This paper will use both terms: conversion rate and market quality, as the context unambiguously reveals the term's meaning.

In addition, one could ask whether these conversion rates are known to the publisher. Do game companies know, for example, the conversion rates from Google? While in reality, the publisher may not know the conversion rates with certainty, past experience will likely provide a good understanding of the market. In addition, information can be obtained from the public domain (see, for example, Table 7 in Section 6). While our model assumes the conversion rates to be known, one could add uncertainty to the parameters, which decreases as the game progresses. However, such an extension is beyond the scope of this paper.

Satiation, *CLV*, and *RSV*: Customer satiation leads to lower customer engagement with the product as users spend less time in the game and are thus less exposed to advertising and in-app purchases. Under satiation, customers will be more likely to churn. Thus, satiation can affect the two fundamental components of customer profitability: per-period gross margin (g), and retention probability (r). Hence, the values of g and r are only starting values. We assume a declining expected profit pattern and retention due to satiation in the following functional form, where $\delta \leq 1$, and $\mu \leq 1$:

$$\begin{Bmatrix} g(t) = g \cdot \delta^{t-1} \text{ for } t \geq 1 \\ r(t) = r \cdot \mu^{t-1} \text{ for } t \geq 1 \end{Bmatrix} \tag{1}$$

Note that when a customer is transferred, a new satiation process starts. The *behavioral resetting mechanism* from a satiated customer to a customer who begins a new satiation process is an essential source of profitability increase that drives cross-promotion. If the firm's discount rate per period is d, the expected profitability over time follows from Table 5, where churn occurs at the beginning of each period. Note that in our analysis, we assume a discount rate of zero due to mobile games' short lifecycles. Satiation influences two basic profitability measures: The expected CLV of a customer just acquired (*CLV*), and her residual value (*RSV*). The expected CLV of a new customer under satiation is, therefore:

$$CLV_{1\to\infty} = \frac{rg}{1 + d - \delta\mu r} \tag{2}$$

At time T, a customer's remaining lifetime value, which we label the residual lifetime value (RSV), for the seller, is:

$$RSV_{T\to\infty} = (\delta\mu)^T \frac{rg}{1 + d - \delta\mu r} = (\delta\mu)^T CLV_{1\to\infty} \tag{3}$$

Equation (3) shows that *RSV* takes into account the satiation-driven decay that the customer undergoes up to T. Note that this analysis is performed at time T, when the transaction takes place. Thus, *RSV* assumes that the customer is still active, i.e., that the customer has been retained so far. If the game developer seeks to find out the residual value when it acquires a customer (Time 0), then the odds of the customer staying as an active user should be considered. In this case, the value would be $r^T(\delta\mu)^T CLV_{1\to\infty}$. However, when calculating the transaction value at time T, both buyer and seller already know that the customer is still active, so no conditional probability is needed.

Optimal Satiation: The extent to which customers exhibit satiation will depend upon the game's characteristics and any possible influence of customer characteristics. For example, games with a unique concept, a more challenging in-game experience, or a competitive character are likely to be more engaging over a longer period, leading to less satiation. Suppose there is no cost in developing and publishing a game with low satiation. In that case, the problem is trivial: The firm will only publish games with high δ and μ (implying low satiation) – ideally.

$\delta = \mu = 1$– which maximizes the CLV expressed in Equation (2). In what follows, we assume that the cost of managing satiation follows a quadratic shape:

$$C(\delta\mu) = \frac{1}{2} c (\delta\mu)^2 \tag{4}$$

The firm thus faces optimizing the following profit function:

$$\pi = CLV_{1\to\infty} - C(\delta\mu) = \frac{rg}{1 + d - \delta\mu r} - \frac{1}{2} c (\delta\mu)^2 \tag{5}$$

In Web Appendix A, we show that when the firm chooses a satiation level subject to a quadratic cost structure, there is a cost level $\bar{c}$ such that for $c > \bar{c}$ there exists a unique internal solution $\delta^* = \mu^* < 1$ that maximizes profit, while for $c \leq \bar{c}$ the firm chooses the boundary condition $\delta^* = \mu^* = 1$. We also show that the optimal level of satiation δ^* increases in gross profit, cost of design, and underlying retention, that is:

$$\partial\delta^*/\partial g \geq 0, \text{ and } \partial\delta^*/\partial r \geq 0 \tag{6}$$

Thus, for the remainder of our analysis, we assume that satiation follows the optimal level specified in Web Appendix A. Moreover, as the case of $\delta^* = \mu^* = 1$ is hardly of interest, we assume that the cost parameter c is higher than the threshold level, thus $\delta^* = \mu^* < 1$.

Decision space: We next examine the potential benefit of the buyer and the seller under the three options that the buyer has at her disposal: *acquisition* (from outside sources such as Google or Facebook), *purchase* (from another game publisher in the inside market, which we label the *seller*), or *swap* (with another game publisher in the inside market).[2]

4.1. Buyer Option 1 – Acquisition from the Outside Market: Facebook & Google

Acquisition sources on the outside market are external entities such as Google, Facebook, or Snap, through which a buyer can acquire new users. Google and Facebook alone represent nearly half of all game advertising investment, and games are considered a significant source of income for these two platforms (Seufert 2019). The strength of these outside market sources derives from the comprehensive view of their users' behavior in out-of-game environments and intelligent targeting algorithms that enable them to reach potential users. When approaching the outside market, the buyer considers the customer acquisition cost (*CAC*) and the conversion rate.

[2] In Appendix 1, we show the conditions under which the market breaks down and no exchange takes place.

Table 5
Expected profit of an app with satiation δ and..$\boldsymbol{\mu}$

$\boldsymbol{t}=1$	$\boldsymbol{t}=2$	$\boldsymbol{t}=3$	$\boldsymbol{t}=\boldsymbol{T}$
$g\frac{r}{1+d}$	$rg\delta\frac{r\mu}{(1+d)^2}$	$rg\delta^2\frac{r^2\mu^2}{(1+d)^3}$	$rg\delta^{T-1}\frac{r^{T-1}\mu^{T-1}}{(1+d)^T}$

Customer acquisition cost (CAC) is the sum paid to the advertising provider of the outside market. Outside market sources typically have a price for customer acquisition (which can be fixed or based on auctions) regardless of the specific advertiser, so CAC is exogenously determined by the game we analyze. We assume that the effective expected CLV for the outside market prospect will be the industry-level CLV multiplied by β with $0 \leq \beta \leq 1$. Overall, the buyer's marginal benefit after acquiring a customer from the outside is:

$$Benefit_{B1} = \beta CLV - CAC \tag{7}$$

Thus, for simplicity in the following analysis, CAC is fixed. Section 6 examines a case wherein CAC is a function of conversion probability, and shows that our basic results still hold.

4.2. Buyer Option 2 – Purchase from the seller on the inside market: A screening mechanism

Instead of relying on the outside market, the buyer can approach the inside market of other game publisher and pay in exchange for a customer. Playing a game indicates specific preferences and serves as a *screening mechanism* for other games seeking customer acquisition. Given the large number of potential sellers and buyers in the market, and the difficulty efficiently connecting them, advertising networks can mediate among publishers and advertisers. Using large quantities of data on individual users and on the needs, availability, and history of the publisher's customer base, ad networks can use data science to optimize advertising beyond the capabilities of the typical publisher or advertiser (Dogtiev 2020a). When approaching the inside market, the buyer considers two factors: the purchase acquisition cost (PAC), and the conversion rate of the inside market.

The purchase acquisition cost is the sum the buyer must pay for a customer that installs the game (we show later that it results from the equilibrium conditions). We use the label PAC to differentiate it from the customer acquisition cost on the outside market. Purchase from the seller on the inside market occurs if the buyer prefers purchasing over acquiring on the outside market. and the seller prefers selling over swapping. In this case, the buyer pays the seller the purchase acquisition cost (PAC). From the seller's perspective, the PAC is equal to the "salvage value" of the customer at time T, when the exchange occurs.

As before, one can view α as a conversion rate representing the ability to capture high-level customers from the inside market. The question here is how much playing in one game serves as a helpful screening mechanism. The similarity between the games plays a role: If the seller's game is similar to the buyer's in terms of the player's characteristics and preferences, then the seller can expect higher quality customers α, which will raise the effective CLV. The marginal benefit for the buyer after the second option of purchasing in the inside market is thus:

$$Benefit_{B2} = \alpha CLV - PAC \tag{8}$$

4.3. Buyer Option 3 – Swap with the seller on the inside market: Saving on out-of-pocket costs

Customer swap also occurs among players in the inside market. However, in a swap, the buyer pays the seller not by transferring PAC, but rather by providing the seller access to its customers. By doing so, the buyer becomes a seller, and de facto customers can be "swapped.".

Customer swap occurs in practice in two ways: direct, or via an app network exchange (Dogtiev 2020b; Rankmyapp 2019). In direct cross-promotion, two apps connect directly and agree to send each other traffic. Large advertising networks may enable brands that work with them to use their database to search for potential partners for free as part of their service. This activity will be associated with some transaction costs of finding the right partner of mutual interest and drafting the agreement. An app network exchange is a platform such as Tappx or Tapdaq that mediates between the sides (Salz 2015, Banis 2018). The platform can use its data science market knowledge to offer informed matches to potential game publishers and save on negotiation costs. The platform provides credit to a focal app for allowing other apps to advertise in them, and in exchange, the focal app can use the credit to advertise itself in other apps. As the buyer gives away its current customer, whose value is RSV, the swap's marginal benefit is:

$$Benefit_{B3} = \alpha CLV - RSV \tag{9}$$

The Seller Options: Market transaction can only occur in cases where both sides benefit. This has two implications: First, it is conceivable that none of the aforementioned options is appealing to the buyer. In this case, the buyer may decide that it is not worth paying for additional customers and, consequently, forgo the decision to gain a new customer. Second, for Options 2 and 3, which occur on the inside market, the seller must find the deal appealing. We, therefore, have to consider the seller's benefit as well.

Like the buyer, the seller has three options: Option 1 is to keep the customer and not engage in an exchange with the buyer. This will occur if the buyer approaches the outside market or decides not to invest in acquisition at this stage. Option 2 is to transfer the customer to the buyer on the inside market. In this case, the seller obtains the purchase acquisition cost *PAC* from the buyer, yet loses the value of the current customer *RSV*. However, to maintain the level of market activity and render the comparison to other options valid, the seller also needs to acquire a customer on the outside market in exchange for the customer acquisition cost *CAC*. Option 3 is to swap the customer with the buyer if the buyer is interested in a swap, where the benefit for the seller is the value of the new customer, minus the value of the current one. The benefits of these three options to the seller are as follows:

$$Benefit_{S1} = 0 \tag{10}$$

$$Benefit_{S2} = PAC - RSV + \beta \cdot CLV - CAC \tag{11}$$

$$Benefit_{S3} = \alpha CLV - RSV \tag{12}$$

5. When do we expect cross-promotion to occur?

In this section, we analyze the equilibrium and identify the conditions under which cross-promotion occurs. Once it does, we identify the conditions under which either selling or swapping is optimal. To find these conditions, we first have to find the equilibrium condition of the purchasing acquisition costs (*PAC*), as this has crucial implications for both buyer and seller. While Appendix A specifies the exact parameter constraints for each of these conditions, we focus here on purchasing on the inside market that determines its price. For purchasing on the inside market to occur, we need the following four conditions:

1. The buyer prefers purchasing from the inside market over acquiring on the outside market.
2. The buyer prefers purchasing over swapping.
3. The seller prefers selling over keeping the user.
4. The seller prefers selling over swapping.

Condition (1) implies an upper bound on *PAC* as per Equations (8) and (7):

$$Benefit_{B2} \geq Benefit_{B1} \ \text{ or } \ \alpha CLV - PAC \geq \beta CLV - CAC$$

Similarly, Condition (4) implies a lower bound on *PAC* as per Equations (11) and (12):

$$Benefit_{S2} \geq Benefit_{S3} \ \text{ or } \ PAC - RSV + \beta CLV - CAC \geq \alpha CLV - RSV$$

Both inequalities imply:
$\beta CLV - CAC = \alpha CLV - PAC$ or:

$$PAC = (\alpha - \beta) \cdot CLV + CAC = \alpha CLV - (\beta CLV - CAC) \tag{13}$$

Equation (13) shows that the purchase acquisition cost of a customer reflects the difference between the value the seller supplies to the buyer (αCLV) and the value the buyer can get in the outside market alternative ($\beta CLV - CAC$). This renders the customer's salvage value different from other customer profitability measures such as *CLV* that focus on the customer and her relationship with the firm, as *PAC* takes into account the interplay of two entities: the buyer, and the seller. While the customer relationship with the firm (*CLV*) is part of the salvage value calculation, so is the extent to which the customer fits a prospective buyer (α), the quality of the alternative market for the buyer (β), and the alternative acquisition cost (*CAC*).

Conversion Rates and the Decision to Cross-Promote: Conditions (1) and (4) specify the exact price of the exchange between the seller and the buyer (*PAC*). Similarly, for swapping, we obtain $\alpha CLV \geq RSV$. We label the expected market outcomes – acquisition, purchase, swap, and no action – as the *customer buying zones*. Fig. 2 depicts the various customer buying zones, where the vertical axis represents the outside market conversion rate (β), and the horizontal axis the inside market conversion rate (α).

The *inside market conversion rate threshold* is defined by $\alpha_T = RSV/CLV$, i.e., the relative residual value of the current customer, defined as the fraction of residual value of the *CLV*. If the inside market conversion rate is high (i.e., above the threshold), the equilibrium outcome is purchase/sale at *PAC*, or swap. The intuition here is that a high-quality inside market indicates that the seller's screening is valuable for the buyer, rendering the acquisition of a screened (vs random) customer more beneficial. However, if the inside market conversion rate is low (i.e., below the threshold), screening has only a limited value. The choice is between acquiring a random/unscreened customer on the outside market, or no action.

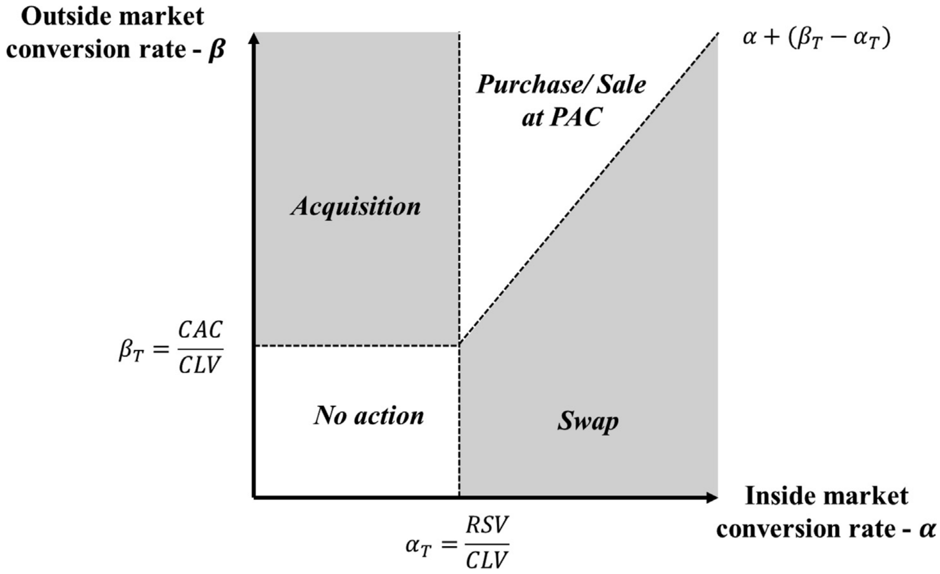

Fig. 2. Market Equilibrium Outcomes.

The *outside market conversion rate threshold* is defined by $\beta_T = CAC/CLV$, i.e., the relative customer acquisition cost on the outside market, defined as the fraction of customer acquisition cost of *CLV*. In the case of low inside market quality, where the choice is between acquisition on the outside market and no action, acquisition only occurs when the outside market's quality is sufficiently high. The intuition here is that a buyer would only acquire a customer on the outside market if the expected benefit (β *CLV*) is above the cost of such an acquisition (*CAC*). If this is not the case, then the buyer prefers no action over acquisition.

The diagonal line represents a second threshold of the outside market conversion rate defined by $\alpha + (\beta_T - \alpha_T) = \alpha - \frac{RSV - CAC}{CLV}$. The line has a fixed slope of 1, and an intercept equal to the difference between the relative customer acquisition cost and relative residual value.

$(\beta_T - \alpha_T)$. If the inside market conversion rate is high, the choice is between purchase and swap. A purchase occurs if the outside market quality is high (above the threshold), and a swap if it is low (below the threshold). The intuition here is that in the case of a purchase, the seller must acquire a new customer on the outside market to replace the sold customer. Hence the outside market quality becomes essential. As the buyer has to forego *RSV* and the seller has to acquire a new customer on the outside market for *CAC*, the relevant threshold needs to take both variables into account.

Proposition 1. *In equilibrium, the game publisher cross promotes when the quality of the inside market is above a given threshold, regardless of the quality of the outside market. The outside market comes into play when deciding whether to swap (if the quality of the outside market is lower than that of the inside market) or purchase from a rival.*

Proof of Proposition 1. The proof rests on Table 6, which summarizes the results of Fig. 2. As $\alpha_T = RSV/CLV$ is independent of the outside market's quality β, it implies that the decision to cross-promote is related to the size of α relative to α_T only. On the other hand, the decision to purchase on the inside market or to swap depends upon both levels of inside and outside market qualities given by the size of β relative to $\alpha + (\beta_T - \alpha_T)$.

Market Factors and the Decision to Cross-Promote: Next, we consider the outside and inside market quality thresholds that govern switches among the various customer buying zones in Fig. 2. For the outside market quality, the threshold is the relative acquisition cost of the buyer in the outside market (*CAC*/*CLV*). This relative acquisition cost is a well-established measure across industries to assess customer acquisition (Oba 2017). The threshold for inside market quality is the relative cost of letting go of the customer to the seller (*RSV*/*CLV*). Using the expressions for *CLV* and *RSV* in Equations (2) and (3) results in the following expressions:

$$\alpha_T = \frac{RSV}{CLV} = (\delta\mu)^T \quad (14)$$

$$\beta_T = \frac{CAC}{CLV} = CAC\frac{1 + d - \delta\mu r}{rg} \quad (15)$$

Table 6
Summary of Market Equilibrium Outcomes.

	Acquisition from the Outside Market	Cross Promotion: Purchase from Seller on the Inside Market	Cross Promotion: Swap with the Seller on the Inside Market
Conversion rate of the inside market (α)	$\alpha \le \alpha_T$	$\alpha \ge \alpha_T$	$\alpha \ge \alpha_T$
Conversion rate of the outside market (β)	$\beta \ge \beta_T$	$\beta \ge \alpha + (\beta_T - \alpha_T)$	$\beta \le \alpha + (\beta_T - \alpha_T)$
Costs to the buyer per one user	CAC	$PAC = (\alpha - \beta) \cdot CLV + CAC$	RSV

* $\alpha_T = RSV/CLV$, and.$\beta_T = CAC/CLV$

Given Proposition 1, the inside market threshold (Equation (14)), which is driven by users' satiation, governs the decision to cross-promote.[3] The seller's benefit from selling on the inside market, considering the price paid, is αCLV, and in exchange for this benefit, the seller gives up RSV in return. At the time of customer acquisition, the seller does not have an incentive to transfer the customer as satiation has not yet materialized, and the customer's residual value for the seller is still too high. Over time satiation will become more pronounced, rendering transfer more appealing to the seller. In the absence of satiation ($\delta = \mu = 1$), the inside threshold becomes 1, meaning there is no inside market. Cross-promotion (through either selling or swapping) therefore occurs only when under satiation.

We can now also further examine the market factors that affect satiation. We have seen (from Equation (6) and Web Appendix A) that the satiation parameter is higher (and hence satiation lower) if (a) gross profit margins increase, (b) the cost of designing games decreases, and (c) the retention probability increases. Thus, these market factors will also affect the decision to cross-promote. Proposition 2 summarizes the sensitivity of cross-promotion to the market conditions:

Proposition 2. *In equilibrium, the likelihood of observing cross-promotion (either selling to or swapping a user from a rival) increases in satiation and decreases in retention.*[4] *It also decreases in gross profits and increases in the costs of designing a game.*

Proof of Proposition 2. Fig. 2 shows that all equilibrium outcomes correspond to areas in a square defined by α and β. As both α and β are between 0 and 1, the total size of that square is 1. Therefore, we can interpret each area's size as a measure of how likely a specific outcome is to occur. Using this approach, we define A as the likelihood of observing outside acquisition in equilibrium, P as the likelihood of observing inside purchase/sale at PAC at equilibrium, S as the likelihood of observing swap at equilibrium, and $CP = P + S$ as the likelihood of observing any form of cross-promotion (either selling or swapping). It is straightforward to calculate the areas of these shapes in Fig. 2 to come up with the following (in Web Appendix B, we provide another scenario wherein the line $\alpha + \beta_T - \alpha_T$ cuts the $\alpha = 1$ line above 1, and in this scenario, the sizes of S and P are different):

$$\begin{cases} A = \alpha_T(1 - \beta_T) \\ S = \beta_T(1 - \alpha_T) + 0.5(1 - \alpha_T)^2 \\ P = (1 - \alpha_T)(1 - \beta_T) - 0.5(1 - \alpha_T)^2 \\ CP = 1 - \alpha_T \end{cases} \tag{16}$$

The proof follows chain differentiations of these quantities (see Web Appendix B for details).

Market Factors and the Decision to Sell or Swap: While Proposition 2 investigates the conditions for cross-promotion (agnostic to selling or swapping), Proposition 3 looks at the case wherein the firm decides to cross promote, and then wonders if it should sell or swap. This decision depends upon the value of the diagonal line in Fig. 2, which separates swapping and selling. This decision is summarized in the following proposition.

Proposition 3. *In equilibrium, given that the firm has decided to cross-promote, the likelihood of observing swapping decreases with gross profits and retention and increases with the cost of designing a game.*

Proof of Proposition 3. The proof follows Equation (16) and a chain differentiation of the terms S and P with respect to g, r, and c (see Web Appendix B). For example, to see the effect of retention, observe the following sequence (similarly for other parameters): An increase in retention decreases satiation (increases δ), which in turn increases the threshold of the inside market quality (α_T) and decreases the threshold of the outside market quality (β_T), the latter also decreasing directly via

[3] As we showed above when discussing optimal satiation, there is no difference in the effect in this context between the retention satiation δ and the usage satiation μ. When we use "satiation", we refer to both.

[4] This result is consistent with the empirical observation we presented in the motivating example.

the increase in retention (see Equation (13)). An increase in the threshold of the inside market quality (α_T) decreases the likelihood of swap (as the latter requires the inside market quality to be greater than this threshold). Similarly, a decrease in the outside market quality threshold decreases the likelihood of a swap (see Fig. 2). Thus, this sequence that began with an increase in retention decreases the likelihood of a swap.

The Effect of Blacklisting on the Ubiquity of Cross Promotion: The emergence of inside markets confronts managers with critical issues that are less relevant in outside markets. One of them is blacklisting, a common practice in the mobile gaming industry of preventing the promotion of specific apps or apps belonging to specific categories. In most cases, blacklisting is engaged in by advertisers due to issues of the low quality of customers in terms of CLV for specific apps or categories of apps (Kim 2020, Digital Limbo 2019). More frequently, blacklisting is used when apps want to avoid churn of high-value customers or when apps believe that for some advertisers, they can benefit from the advertising revenue, yet keep their customers. Some market observers criticize the act of blacklisting. Specifically, it has been argued that (a) users will churn anyhow, and blacklisting just decreases their value because it limits the options for cross-promotion; (b) a "blacklisting war" will decrease revenue to all sides; and (c) apps can work instead on targeting that will ensure that just the right customer will see the ad (Digital Limbo 2019). While such claims can certainly be valid in some cases, our formal framework enables us to look at the situation differently, as summarized by the following proposition:

Proposition 4. *Blacklisting, a common tactic in the mobile game industry that prevents the cross-promotion of specific apps, will increase the likelihood of cross-promotion (either purchasing or swapping a user from a rival).*

Proof of Proposition 4. Though we have assumed a homogenous inside market, an alternative assumption is to assume a distribution in market quality, and that cross-promotion efforts hit one random person within this distribution. Formally this is reflected in the assumption that inside market quality follows a, e.g., uniform distribution with $\alpha \sim U(a_{min}, a_{max})$, and thus define $\bar{\alpha}$ as the mean of this distribution $\bar{\alpha} = (a_{min} + a_{max})/2$. Blacklisting involves restrictions on swapping customers from the inside market whose quality is low, reflected in $\bar{\alpha}$. Specifically, the app developer blocks the low end of the distribution. Assuming that blacklisting is effective, there is a new lower bound of the distribution $\alpha^{bl}_{min} > a_{min}$. This in turn implies a new mean of the distribution $\bar{\alpha}^{bl} > \bar{\alpha}$. No other parameter is affected by this, including α_T. From Table 6, we conclude that a larger α implies a higher likelihood of satisfying the condition $\alpha \geq \alpha_T$, thus increasing the likelihood of cross-promotion.

Timing boundaries: Although our game is not dynamic, we can inquire about the boundary of the time when these transactions occur: Table 4 implies that purchasing from the seller on the inside market at a price of *PAC* occurs when a) $\alpha \geq \alpha_T$; and b) $\beta \geq \alpha + (\beta_T - \alpha_T)$, where $\alpha_T = (\delta\mu)^T$, and $\beta_T = \frac{CAC}{CLV}$. This implies that the equilibrium conditions place a constraint on *T* to be $\alpha \geq (\delta\mu)^T \geq \alpha + \beta_T - \beta$.[5]

Differentiation of the boundaries of *T* yields that both are increasing in δ and μ and decreasing in α. This yields the following intuitive interpretation: Recall from Equation (8) that the seller's benefit from selling on the inside market, after plugging in the price *PAC*, is αCLV. In exchange for this, the seller is giving up *RSV*. At the initial time (of acquisition of the customer), the seller does not have an incentive to transfer the customer, as satiation has not yet materialized, and the residual value of the customer for the seller is still too high (at $T = 0$, *RSV* is equal to *CLV*). Over time satiation becomes more pronounced, which lowers *RSV* and renders transfer more appealing to the seller. Looking at the other side of the exchange, the buyer does not want to purchase too late, as her net benefit correlates with *RSV,* which is falling with time.

6. Extensions

Market Expansion: Our main model assumes that under cross-promotion, the seller must have lost a customer if a buyer gains a customer. In reality, the case could occur wherein customers play both games simultaneously, resulting in market expansion. Recall that the users' engagement, as measured in playing time, is fast declining. Thus, even if the user keeps playing the old game, we could expect a further decline and a short average stay. In our main setting, the publisher loses *RSV* when the user stops playing the game at the transfer time. Under market expansion, the publisher keeps a share of that revenue stream, which can be expressed as λRSV for $0 \leq \lambda \leq 1$. Intuitively, this should make selling and swapping more appealing, as the loss of the customer is only partial. This intuition is proven in the next proposition:

Proposition 5. *Under market expansion, when users play both games simultaneously, in equilibrium, the likelihood of observing cross-promotion (either selling to or swapping a user from a rival) increases as compared with a single game use, and within cross-promotion, swap is more likely than purchase at PAC.*

Proof of Proposition 5. Following the steps used in the construction of the equilibrium in Section 4, the benefits of the buyer and seller in the new setting are summarized in the following:

[5] To show that this is not an empty set, note that we have to show that $\alpha \geq \alpha + \beta_T - \beta$ or equivalently that $\beta - \beta_T \geq 0$. From condition b) above we know that $\beta \geq \alpha + (\beta_T - \alpha_T)$, that is, $\beta - \beta_T \geq \alpha - \alpha_T \geq 0$, where the last inequality follows from condition a) above.

Buyer:

(7a) (Acquire outside).$Benefit_{B1} = \beta CLV - CAC$
(8a) (Purchase inside).$Benefit_{B2} = \alpha CLV - PAC$
(9a) (Swap).$Benefit_{B3} = \alpha CLV - RSV + \lambda RSV$

Seller:

(10a) (Do nothing).$Benefit_{S1} = 0$
(11a) (Sell inside). $Benefit_{S2} = PAC - RSV + \beta CLV - CAC + \lambda RSV$
(12a) (Swap). $Benefit_{S3} = \alpha CLV - RSV + \lambda RSV$

With these revised equations, it's straightforward to see that our analysis in Appendix 1 holds unchanged with the term $(1-\lambda)RSV$ replacing the term RSV throughout the analysis. Fig. 2 now becomes Fig. 2a. This figure shows that with $0 \leq \lambda \leq 1$, the likelihood of observing cross-promotion increases, and within cross-promotion, swap becomes more likely.

Customer Acquisition Costs and Conversion Rates: Customer acquisition cost (*CAC*) is the cost paid to the likes of Facebook or Google that provides customer acquisition from the outside market, whose conversion rate is given by β. *CAC* cannot be made endogenous within our model, as the game publishers are small and cannot influence, let alone control, the pricing mechanisms of Google and Facebook. However, the price of the good (advertising) should be related to its quality, and thus *CAC* should be related to β. We assume a log-linear relationship, and thus for some parameter γ:

$$CAC = \text{constant} \cdot \beta^{\gamma} \tag{17}$$

Somewhat counterintuitively, there are reasons to believe that the relationship between *CAC* and the conversion rate is *negative*, that is, $\gamma \leq 0$ (we will presently assume that the constant of Equation (17) is one). First, from a theoretical point of view, note that if Facebook determines both quality and price, there is no causality implied by the relationship of Equation (17), and the relationship might very well be negative.[6] Second, from an empirical point of view, observe Table 7, which shows the relationship between the average Google display advertising cost per conversion and the conversion rates in various industries Bond (2022).

The correlation between average Google ad cost per conversion and the conversion rates is negative (-0.86). Moreover, if we take the same tables for Facebook ads and Google Search ads (also in Bond (2022)) and run a pooled regression of the three datasets using Equation (17), we find that the regression fits the data relatively well (R-Squared of 70 %) and that $\gamma = -0.52$, and is significant at the 99 % level.

There are at least two reasons for this negative correlation between *CAC* and conversion: First, Google and Facebook established a measure of ad quality called Quality Score and Relevance Score respectively, such that the higher the score, the higher the conversion rate and the lower the ad cost (see Finn 2020). Second, *CAC* is computed retroactively by taking the entire advertising budget and dividing it by the total number of new users. Given a slight decline in the conversion rate, the calculated *CAC* increases.

To replicate the analyses of the equilibrium outcomes and Web Appendix B, without loss of generality, let the constant of Equation (17) be one, and thus $CAC = \beta^{\gamma}$. The analysis remains largely unchanged, except for Table 8, which now replaces Table 6. In addition, if $\gamma \leq 0$, the analysis remains the same without additional constraints, while if $\gamma \geq 0$, additional constraints are needed as follows: If $\gamma \leq 0$, then $\partial F/\partial\beta > 0$, and the analysis goes through. However, if $\gamma \geq 0$, we need a lower bound on *CLV* to ensure that $\partial F/\partial\beta > 0$, that is, $CLV > \gamma\beta^{\gamma-1}$.

The lower bound on *CLV* is a binding constraint for the rest of the propositions: In Web Appendix D, we replicate the sensitivity analyses of Web Appendix C, when *CAC* and β are correlated, where we show that all our four propositions can be replicated if $CLV > 1$ and $\gamma \leq 1$.

Internal Cross Promotion: Transfer Price and Partial Resetting: Internal cross-promotion represents the case wherein a customer is transferred to another brand within the same publisher's brand portfolio. Many mobile game publishers are creating a portfolio of games to ensure that the satiated customers of one brand will become the new customers of another brand. In our interviews with mobile game publishers, we found that many game publishers (though not all) manage the various games as separate profit centers, with brand managers controlling marketing, as in FMCGs. In this case, the price *PAC* paid for purchase in the internal market corresponds to a transfer price between two departments (Hamamura 2019).

In this case, our analysis holds with one caveat related to the similarity of the games within one publisher, which we will discuss shortly. In the case wherein the various mobile games are not managed as profit centers, the logic of transfer pricing cannot be applied, as it requires the two departments to act independently. There is, therefore, no mechanism to determine *PAC*. Our analysis still holds, as from Appendix 1, without the possibility of purchase on the internal market, swapping is preferable to acquiring on the outside market if β is small, that is:

[6] To see this, assume a loglinear demand function of a firm that sets both quality (q) and price (p) simultaneously so that it maximizes profits given by:$\pi = (p-c)p^{-a}q^{b} - q^{2}/2$, where c is the production costs, and a and b are price and quality elasticities. First-order conditions imply that $p = \text{constant}\cdot q^{\gamma}$, where $\gamma = (2-b)/(1-a)$. Second-order conditions imply that $\gamma < 0$.

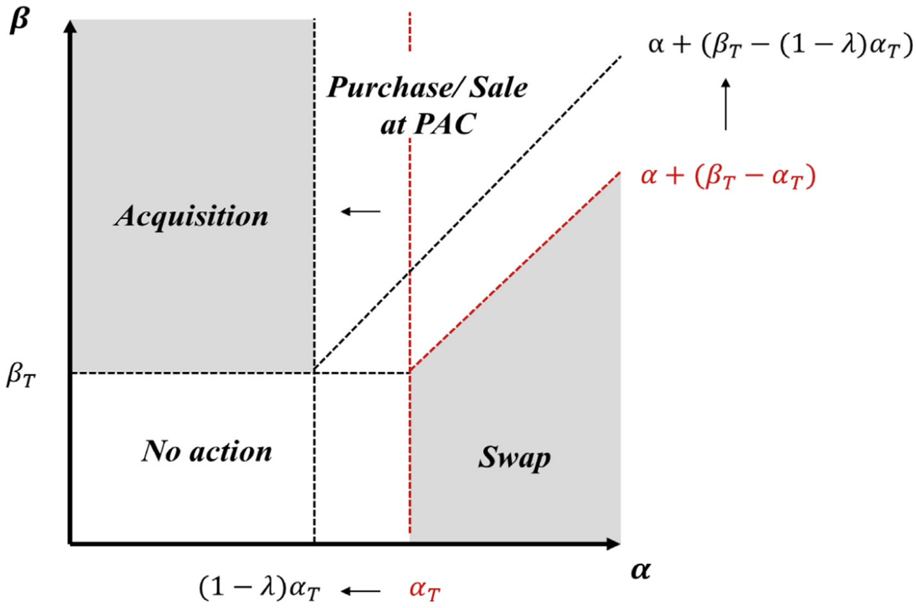

Fig. 2a. Market Equilibrium Outcomes.

Table 7
Google Advertising Conversion Rates and Cost per Conversion (Display Ads)*.

Industry	Average Google advertising conversion rates	Average Google advertising cost per conversion
Apparel	0.58 %	$62.8
Arts & Entertainment	0.75 %	$70.6
Business & Industrial	0.29 %	$152
Computers & Electronics	0.50 %	$124.6
Dining & Nightlife	0.56 %	$81.5
Finance	0.80 %	$84.1
Health	0.75 %	$101.5
Hobbies & Leisure	1.12 %	$35.4
Home & Garden	0.35 %	$129.1
Jobs & Education	0.38 %	$123.8
Law & Government	0.46 %	$133.4
Real Estate	0.36 %	$110.1
Retailers & General Stores	0.53 %	$99.6
Sports & Fitness	0.80 %	$60.9
Travel & Tourism	0.39 %	$115.4
Vehicles	0.51 %	$119.6
Correlation between conversion rates and advertising costs	**−0.86**	

* Source: Bond (2022).

Table 8
Market Equilibrium Outcomes when *CAC* depends upon outside market quality β*.

		Cross Promotion	
	Acquisition from the outside market	**Purchase from seller on the inside market**	**Swap with seller on the inside market**
Quality of the inside market (α)	$\alpha \leq \alpha_T$	$\alpha \geq \alpha_T$	$\alpha \geq \alpha_T$
Quality of the outside market (β)	$\beta \geq \beta_T$	$F(\beta) \geq \alpha - \alpha_T$	$F(\beta) \leq \alpha - \alpha_T$
Costs to the buyer per one user	*CAC*	$PAC = (\alpha - \beta) \cdot CLV + \beta^{\gamma}$	*RSV*

* $F(\beta) = \beta - \beta^{\gamma}/CLV$. Note that as $\partial F/\partial\beta > 0$, it follows that the inequalities of $F(\beta)$ imply inequalities of β in the same direction, that is, $F(\beta) \geq \alpha - \alpha_T$ implies $\beta \geq F^{-1}(\alpha - \alpha_T)$.

$$\alpha CLV - RSV \geq \beta CLV - CAC \tag{18}$$

If β is large, acquiring on the outside market is preferable (in both cases, these quantities should be positive).

As the same publisher produces multiple games, we can expect some similarities between them. Thus, our assumption of a full reset of engagement does not necessarily hold. Generally, we expect a negative correlation between game similarity and customer reset. The more similar the games are, the less reset we are likely to observe. This is reflected in Proposition 6:

Proposition 6. *If the same publisher produces multiple games, the more similar the games, the less the resetting value of cross-promotion, with a resultant decrease in cross-promotion. Moreover, if the games are not set up as profit centers, purchase on the internal market is not an option; only swap is available as a cross-promotional tool.*

Proof of Proposition 6. The second part of the proposition was proven via Equation (18). For the first part, note that similarity relates to the role of cross-promotion as a useful screening mechanism for another game. If the seller's game is similar to the buyer in terms of the players' characteristics and preferences, then the seller can expect a higher quality customer α, which will raise the effective *CLV*. Suppose we denote the fraction we have used so far (α) because of screening α^{screen}, and recall that we denoted the resetting fraction by α^{reset}, then the publisher on the receiving end of swapping or selling would receive a value of $\alpha^{new}CLV$, where $\alpha^{new} = \alpha^{screen} \cdot \alpha^{reset}$. The rest of the analysis now goes through this new inside market quality, with α^{new} replacing α. As $\alpha^{new} \leq \alpha$, the net result would be a decrease in cross-promotion.

7. Discussion

Historically, marketers looked at customer acquisition through an outside market lens where buyers consider customer acquisition cost, conversion rates, and customer lifetime value when making acquisition decisions (Peters, Verhoef, and Krafft 2015). The emergence of an inside market where firms sell and swap customers, demands a broader view. The mobile gaming industry, where satiation coexists with efficient customer management abilities, is a perfect context for examining these new dynamics. In such environments, buyers and sellers weigh the inside vs outside market alternatives and within the inside market, selling vs swapping. Our analysis illustrates the dynamics to be considered. It enables us to provide new insights into the market conditions under which cross-promotion occurs and, if it does, the cases wherein selling or swapping is preferred. Next, we discuss some more general aspects that emerge from our analysis.

The Optimal Engagement of Customers: There is increasing recognition in the marketing literature of customer engagement and its contribution to profitability (Kumar & Pansari A., 2016; Gill, Sridhar, & Grewal, 2017). While positive sentiment on the importance of engagement can certainly be justified, there is also a need to examine the optimal level of customer engagement given the associated costs. The case of satiation helps to shed some light on this issue. Satiation, which is a process of decreased engagement, can be affected by the firm through various design efforts, some of which can consider the behavioral findings in this area (Galak and Redden 2018).

Our analysis demonstrates that while there is an optimal level of satiation for the firm, we should consider how the interaction between sellers, buyers, and the outside market might affect it. While recognizing the contribution of engaged customers, a realistic view of optimal engagement will improve both planning decisions and our understanding of why customers are not invested in or engaged with the product. In this regard, one of the more intriguing engagement enhancement techniques is dynamic difficulty adjustment (DDA), which adaptively changes a game to make it easier or more complex, depending on the players' state of mind, e.g., frustration or boredom (Pfau et al. 2020).

A Broader View on Customer Profitability: The shift to an inside market view provides an interesting angle on customer profitability and retention. The importance of avoiding churn (Ascarza et al., 2018) and the need to manage the tradeoff between investments in customer acquisition and retention (Reinartz et al., 2005) have generally taken the view of a single brand, implicitly assuming that the outside market is the only option that the firm faces. Including inside markets requires a more nuanced approach, as churning a customer might be profitable, as it generates the potential for acquiring a better customer replacing a satiated one.

The emergence of inside markets also adds a differing view on addressing unprofitable customers: It is generally accepted that firms may not want to retain some less profitable customers (Haenlein, Kaplan, and Schoder 2006). Consequently, researchers have examined the market conditions and cost structures under which a firm may want to "fire" customers (Shin et al., 2012; Subramanian et al., 2014). We elucidate here that under satiation, even "bad customers" may have begun as "good", and that the possibility of selling and swapping in an inside market is another alternative to deal with the less profitable customers.

Customer Equity: Heterogeneity and Social Influence: The inclusion of inside markets emphasizes the advantages of taking a customer equity look at customer profitability rather than that of an individual lifetime value perspective (Drèze and Bonfrer 2009). The firm maximizes the value of a group of customers that can be transferred and exchanged for other customers, not the value of the individuals *per se*. We focus on transferring individuals to understand the dynamics better and enable a parsimonious analysis. A customer equity perspective will enable better examining how heterogeneity among customers affects the dynamics of cross-promotion. When building the model, we assumed that market quality α and β are taken from a distribution. Understanding the shape of the distribution will enable a more informed decision in multiple cases of cross-promotion.

A notable source of heterogeneity stems from the temporal sorting mechanism of churn. The users who stay longer may differ from those who churned early and have, for example, a higher expected retention probability or engagement (Fader and Hardie 2010). This sorting mechanism may also affect the level of satiation and expected quality of the users for the buyer. Our analysis does not address the measurement issues associated with assessing the value of the parameters. In practice, a Bayesian updating mechanism will be needed to update individual expectations based on an individual's behavior over time. Our understanding of the effect of the churn sorting mechanism coupled with a change in the individual over time is still in its early stages (Fader et al. 2018), and a better understanding of the phenomenon will also help measurement in our context.

A second aspect of the move from an individual-level view to multiple users and customer equity is social value. Individuals create social value when they affect the lifetime value of others (Haenlein and Libai 2013). In gaming, the social value can be driven by word of mouth and network effects, particularly in multiplayer games. It can be visible to users through the popularity tables that encourage new users to adopt. Thus, when moving a user from Game A to Game B, the former may lose some social value, and the latter may gain some. Given the change in social value over the product life cycle (Haenlein and Libai 2013), it may be expected that the later in Game A's life cycle and the earlier Game B's life cycle, the more both sides will find the deal more profitable to adopt. However, the precise measurement of this effect is not trivial. Adding social value considerations to cross-promotion analysis is a promising avenue for future research.

Cross Promotion and Clusters: Our analysis of the utility of restricting cross-promotion (Proposition 4) is consistent with the emerging market structure in mobile game markets. As Fig. 2 shows, swapping becomes increasingly likely the better the quality of the inside market. In situations wherein acquisition on the outside market is costly – which is the case in the hyper-casual segment of the mobile game market – game developers will have an incentive to create a high-quality inside market so as to exclude other games deemed to be of lower quality.

One such strategy is to create games similar to those of competitors. A high degree of similarity implies that the screening performed by the seller is a good indicator of value for the buyer. Such similarity can be expected to lead to clusters on the category level wherein multiple game developers specialize in developing similar games. An empirical indication for this can be found when looking at *Candy Crush Saga*, one of the most successful mobile games. The popularity of this game resulted in the emergence of an entire industry based on the same game philosophy, called tile-matching video games (Match 3 games), which includes dozens of games by various developers. This leads to the conclusion that in categories wherein the cost of acquiring customers on the outside market is high, game developers have an incentive to increase the similarity of games on the inside market, leading to the emergence of clusters of similar games between which users are cross promoted (either purchased or swapped).

Cross Promotion Outside the Mobile Games Industry: One could wonder why we do not see more inside market activities outside the gaming environment, given the ubiquity of satiation. We believe that technology plays an essential role in answering this question. For example, for Fast Moving Consumer Goods (FMCG), consumers are likely to be satiated after frequent consumption of the same brand, leading to variety-seeking behavior and brand switching (Kahn 1995; Wang and Shankar 2017). However, players in FMCG markets do not have the ability (yet) to track customers on an individual basis, track the exact usage of the product by the customer to make recommendations at the right time, or analyze profitability similarly to mobile games.

However, there are other markets that should be relevant. One example is the market for personalized content recommendations in online news outlets, such as the aforementioned Outbrains and Taboola. Other natural candidates come from fast-moving hedonic experiences like music streaming and YouTube videos, where customers can be managed and possibly cross-promoted on a large scale. All these present opportunities to develop inside markets. While satiation is undoubtedly a problem in these and other hedonic experience markets, it is still hard to find an equivalent to the gaming industry in the sophisticated real-time customer management context that will identify satiation, assess lifetime value, and be able to cross-promote where needed efficiently. As more markets acquire these skills and abilities, we expect to observe the process of selling and swapping customers more relevant in an increasing number of markets.

Data availability

The data that has been used is confidential.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Equilibrium conditions

1. **When does selling occur, and at what price?**

We observe a purchase/ sale if the buyer prefers purchasing over acquiring and swapping, and the seller prefers selling over keeping and swapping. This leads to the following four conditions:

Selling Condition (1): The buyer prefers purchasing over acquiring:

(1) $\alpha CLV - PAC \geq \beta \cdot CLV - CAC$
(2) $\beta \leq \alpha - \frac{PAC - CAC}{CLV}$

Selling Condition (2): The buyer prefers purchasing over swapping:

(3) $\alpha CLV - RSV \leq \alpha CLV - PAC$
(4) $PAC \leq RSV$

Selling Condition (3): The seller prefers selling over keeping:

(5) $PAC + \beta \cdot CLV - CAC - RSV \geq 0$
(6) $\beta \geq \frac{RSV + CAC - PAC}{CLV}$

Selling Condition (4): The seller prefers selling over swapping:

(7) $\alpha CLV - RSV \leq PAC + \beta \cdot CLV - CAC - RSV$
(8) $\beta \geq \alpha - \frac{PAC - CAC}{CLV}$

Selling Condition (1) and Selling Condition (4) imply that selling takes place only if:

(9) $\beta = \alpha - \frac{PAC - CAC}{CLV}$
(10) $PAC = (\alpha - \beta) \cdot CLV + CAC = \alpha \cdot CLV - (\beta \cdot CLV - CAC)$

Plugging the equilibrium PAC of Equation (10) into Selling Condition (2) yields:

(11) $(1 - \beta) \cdot CLV + CAC - (1 - \alpha)CLV \leq RSV$
(12) $\beta \geq \alpha - \frac{RSV - CAC}{CLV}$

Plugging the equilibrium PAC into Selling Condition (3) yields:

(13) $\beta \geq \frac{RSV + CAC - \alpha CLV + \beta CLV - CAC}{CLV}$
(14) $RSV \leq \alpha CLV$

Thus, we observe a purchase/sale in equilibrium if $\beta \geq \alpha - \frac{RSV - CAC}{CLV}$ under the condition that $RSV \leq \alpha CLV$. The purchase acquisition cost at equilibrium is $PAC = (\alpha - \beta) \cdot CLV + CAC$.

2. **When does swapping occur?**

Similar to above, swapping occurs under the following four conditions:

Swap Condition (1): The buyer prefers swapping over acquiring:

(15) $\alpha CLV - RSV \geq \beta \cdot CLV - CAC$
(16) $\beta \leq \alpha - \frac{RSV - CAC}{CLV}$

Swap Condition (2): The buyer prefers swapping over purchasing:

(17) $\alpha CLV - RSV \geq \alpha CLV - PAC$
(18) $PAC \geq RSV$

Swap Condition (3): The seller prefers swapping over keeping:

(19) $\alpha CLV - RSV \geq 0$

Swap Condition (4): The seller prefers swapping over selling:

(20) $\alpha CLV - RSV \geq PAC + \beta \cdot CLV - CAC - RSV$
(21) $\beta \leq \alpha - \frac{PAC-CAC}{CLV}$

Note that if Swap Condition (4) holds and Swap Condition (2) holds, then Swap Condition (1) holds as well, as:

(22) $\alpha - \frac{PAC-CAC}{CLV} \leq \alpha - \frac{RSV-CAC}{CLV}$, if
(23) $PAC \geq RSV$

We now plug in the expression of equilibrium *PAC* from Equation (10) into Swap Condition (2):

(24) $(\alpha - \beta) \cdot CLV + CAC \geq RSV$
(25) $\beta \leq \alpha - \frac{RSV-CAC}{CLV}$

Plugging in the expression of equilibrium *PAC* from Equation (10) into Swap Condition (4) yields:

(26) $\alpha CLV \geq (\alpha - \beta) \cdot CLV + CAC + \beta \cdot CLV - CAC$
(27) $0 \geq 0$

All of this implies that if $\beta \leq \alpha - \frac{RSV-CAC}{CLV}$ and $RSV \leq \alpha CLV$, then the equilibrium is swap.

3. **When does acquisition occur?**

Acquiring Condition (1): The buyer prefers acquiring over purchasing:

(28) $\alpha CLV - PAC \leq \beta \cdot CLV - CAC$
(29) $\beta \geq \alpha - \frac{PAC-CAC}{CLV}$

Acquiring Condition (2): The buyer prefers acquiring over swapping:

(30) $\alpha CLV - RSV \leq \beta \cdot CLV - CAC$
(31) $\beta \geq \alpha - \frac{RSV-CAC}{CLV}$

Acquiring Condition (3): The seller prefers keeping over selling:

(32) $PAC + \beta \cdot CLV - CAC - RSV \leq 0$
(33) $\beta \leq \frac{RSV-PAC+CAC}{CLV}$

Acquiring Condition (4): The seller prefers keeping over swapping:

(34) $\alpha CLV - RSV \leq 0$

Acquiring Condition (5): The net benefit of acquiring for the buyer is positive:

(35) $\beta \cdot CLV - CAC \geq 0$
(36) $\beta \geq \frac{CAC}{CLV}$

We now plug in the equilibrium *PAC* from Equation (10) into Acquiring Condition (1):

(37) $\alpha CLV - (\alpha - \beta) \cdot CLV - CAC \leq \beta \cdot CLV - CAC$ or $0 \leq 0$, which is satisfied.

We now plug in the equilibrium *PAC* from Equation (10) into Acquiring Condition (3):

(38) $(\alpha - \beta) \cdot CLV + CAC + \beta \cdot CLV - CAC \leq RSV$
(39) $RSV \geq \alpha CLV$

Note that if Acquiring Condition (4) holds and Acquiring Condition (5) holds, then Acquiring Condition (2) is fulfilled, as:

(40) $\frac{CAC}{CLV} \geq \alpha - \frac{RSV-CAC}{CLV}$, if $RSV \geq \alpha CLV$

We have two conditions on β:

(41) $\beta \geq \alpha - \frac{RSV-CAC}{CLV}$ and $\beta \geq \frac{CAC}{CLV}$

It is easy to see that:

(42) $\alpha - \frac{RSV-CAC}{CLV} \leq \frac{CAC}{CLV}$ if $CLV\alpha \leq RSV$

Therefore:

(43) $\alpha - \frac{RSV-CAC}{CLV} \leq \frac{CAC}{CLV} \leq \beta$

This shows that acquisition takes place if $\beta \geq \frac{CAC}{CLV}$ under the condition that $\alpha CLV \leq RSV$.

Finally, we observe no action of any kind (i.e., neither purchase/sale, nor swap nor acquisition) in equilibrium, when the buyer prefers acquiring over purchasing and swapping, and the seller prefers keeping over selling and swapping, but the net benefit of acquisition for the seller is *negative*. It is easy to see that this is equivalent to the previous case with a change in the last condition. Hence, no action occurs in equilibrium if:

(44) $\beta \leq \frac{CAC}{CLV}$ and $\alpha \leq \frac{RSV}{CLV}$

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2022.12.001.

References

Appel, G., Libai, B., Muller, E., & Shachar, R. (2020). On the monetization of mobile apps. *International Journal of Research in Marketing, 37*, 93–107.

AppsFlyer (2022), "The State of Gaming App Marketing – 2022 edition" https://www.appsflyer.com/resources/reports/gaming-app-marketing/.

Ascarza, E., Neslin, S., Netzer, O., Anderson, Z., Fader, P., Gupta, S., ... Schrift, R. Y. (2018). In pursuit of enhanced customer retention management: Review, key issues, and future directions. *Customer Needs and Solutions, 5*, 65–81.

Ascarza, E., Netzer, O., & Runge, J. (2020). *The twofold effect of customer retention in freemium settings*. SSRN.

Banis, Davide (2018), How this startup transforms mobile games into veritable gold mines. TNW, February 5, https://thenextweb.com/insider/2018/02/06/first-user-acquisition-game-monetization-golden-rule-indie-game-developers/.

Bolton, R. N., Lemon, K. N., & Verhoef, P. C. (2004). The theoretical underpinnings of customer asset management: A framework and propositions for future research. *Journal of the Academy of Marketing Science, 32*(3), 271–292.

Bond, Connor, (2022), Conversion rate benchmarks: Find out how YOUR conversion rate compares. https://www.wordstream.com/blog/ws/2019/08/19/conversion-rate-benchmarks.

Cao, Jingcun, Pradeep K. Chintagunta, and Shibo Li (2021), From free to paid: Monetizing a non-advertising-based app. SSRN.

Caro, F., & Martínez-de-Albéniz, V. (2012). Product and price competition with satiation effects. *Management Science, 58*(7), 1357–1373.

Choi, Hana, Carl F. Mela, Santiago R. Balseiro, and Adam Leary (2020), Online display advertising markets: A literature review and future directions. *Information Systems Research*, forthcoming.

Datta, H., Foubert, B., & Van Heerde, H. J. (2015). The challenge of retaining customers acquired with free trials. *Journal of Marketing Research, 52*(2), 217–234.

Dellarocas, C., Katona, Z., & Rand, W. (2013). Media, aggregators, and the link economy: Strategic hyperlink formation in content networks. *Management Science, 59*(10), 2360–2379.

Digital Limbo (2019), Digital pill: Blacklist in ad monetization. January 19, https://www.digitalimbo.com/blacklist-in-ad-monetization/.

Dogtiev, A. (2020a). Top mobile ad networks 2019. *Business of Apps* https://www.businessofapps.com/guide/top-mobile-ad-networks/.

Dogtiev, A. (2020b). Cross-promotion advertising networks. *Business of Apps* https://www.businessofapps.com/ads/cross-promotion/.

Drèze, X., & Bonfrer, A. (2009). Moving from customer lifetime value to customer equity. *Quantitative Marketing and Economics, 7*(3), 289–320.

Fader, P. S., & Hardie, B. GS. (2010). Customer-base valuation in a contractual setting: The perils of ignoring heterogeneity. *Marketing Science, 29*(1), 85–93.

Fader, P. S., Hardie, B. GS., Liu, Y., Davin, J., & Steenburgh, T. (2018). 'How to project customer retention' revisited: The role of duration dependence. *Journal of Interactive Marketing, 43*, 1–16.

Fang, E., Palmatier, R. W., & Grewal, R. (2011). Effects of customer and innovation asset configuration strategies on firm performance. *Journal of Marketing Research, 48*(3), 587–602.

Finn, Allen (2020), Facebook relevance score: 4 key facts to know. https://www.wordstream.com/blog/ws/2017/09/14/facebook-relevance-score.

Frid, Igal (2019), How hyper casual apps are changing the way games monetize. *AppsFlyer*, November 19, https://www.appsflyer.com/blog/hyper-casual-gaming-ad-monetization/.

Galak, J., & Redden, J. P. (2018). The properties and antecedents of hedonic decline. *Annual Review of Psychology, 69*, (6.1-6.25).

Galak, J., Kruger, J., & Loewenstein, G. (2013). Slow down! Insensitivity to rate of consumption leads to avoidable satiation. *Journal of Consumer Research, 39*(5), 993–1009.

Gill, M., Sridhar, S., & Grewal, R. (2017). Return on engagement initiatives: A study of a business-to-business mobile app. *Journal of Marketing, 81*(4), 45–66.

Gupta, S., & Lehmann, D. R. (2003). Customers as assets. *Journal of Interactive Marketing, 17*(1), 9–24.

Haenlein, M., Kaplan, A. M., & Schoder, D. (2006). Valuing the real option of abandoning unprofitable customers when calculating customer lifetime value. *Journal of Marketing, 70*(3), 5–20.

Haenlein, Michael, and Barak Libai (2013), Targeting revenue leaders for a new product. *Journal of Marketing*, 77 (3), 65-80.

Hamamura, J. (2019). Unobservable transfer price exceeds marginal cost when the manager is evaluated using a balanced scorecard. *Advances in Accounting, 44*(1), 22–28.
Han, S. P., Park, S., & Wonseok, O. h. (2016). Mobile app analytics: A multiple discrete-continuous choice framework. *MIS Quarterly, 40*(4), 983–1008.
Hui, S. K. (2017). Understanding repeat playing behavior in casual games using a Bayesian data augmentation approach. *Quantitative Marketing and Economics, 15*(1), 29–55.
IronSource (2021) Cross Promotion. https://developers.ironsrc.com/ironsource-mobile/air/cross-promotion/#step-1.
Johnson, M. D., & Selnes, F. (2004). Customer portfolio management: Toward a dynamic theory of exchange relationships. *Journal of Marketing, 68*(2), 1–17.
Kahn, B. E. (1995). Consumer variety-seeking among goods and services: An integrative review. *Journal of Retailing and Consumer Services, 2*(3), 139–148.
Karnes, KC (2021), Hyper-casual games: Redefining the future of mobile gaming. CleverTap, https://clevertap.com/blog/hyper-casual-games/.
Kim, Y. (2020). *Effects of removing blacklisting*. AdColony.
Knott, A., Hayes, A., & Neslin, S. A. (2002). Next-product-to-buy models for cross-selling applications. *Journal of Interactive Marketing, 16*(3), 59–75.
Kumar, V., & Pansari A. (2016). Competitive advantage through engagement. *Journal of Marketing Research, 53*(4), 497–514.
Lasaleta, J. D., & Redden, J. P. (2018). When promoting similarity slows satiation: The relationship of variety, categorization, similarity, and satiation. *Journal of Marketing Research, 55*(3), 446–457.
Lee, G. M., He, S. u., Lee, J., & Whinston, A. B. (2020). Matching mobile applications for cross-promotion. *Information Systems Research, 31*(3), 865–891.
Lerner, Ben (2019), User churn in mobile apps: Advertiser blacklisting benchmarks. Soomla.com, January 9, https://blog.soomla.com/2019/01/industry-first-user-churn-in-mobile-apps-advertiser-blacklisting-benchmarks-by-soomla.html.
Lewis, M. (2006). Customer acquisition promotions and customer asset value. *Journal of Marketing Research, 43*(2), 195–203.
Li, S., Sun, B., & Montgomery, A. L. (2011). Cross-selling the right product to the right customer at the right time. *Journal of Marketing Research, 48*(4), 683–700.
Luz, Loren (2019), What we learned from eMarketer's new in-game advertising report. IronSource, https://www.ironsrc.com/blog/emarketer-new-in-game-advertising-report/.
Morgan, Blake (2019), NOwnership, no problem: An updated look at why millennials value experiences over owning things. *Forbes*, Jan 2.
Nelson, L. D., Meyvis, T., & Galak, J. (2009). Enhancing the television-viewing experience through commercial interruptions. *Journal of Consumer Research, 36*(2), 160–172.
Oba, Demi (2017), *CLV* to *CAC* ratio: Calculating and understanding the magic metric. *Smile.io*, https://blog.smile.io/clv-cac-ratio-calculating-the-magic-metric/
Oestreicher-Singer, G., Libai, B., Sivan, L., Carmi, E., & Yassin, O. a. (2013). The network value of products. *Journal of Marketing, 77*(3), 1–14.
Peters, K., Verhoef, P. C., & Krafft, M. (2015). Customer acquisition strategies: A Customer equity management perspective. In V. Kumar & D. Shah (Eds.), *Handbook of Research on Customer Equity in Marketing*. Cheltenham, UK: Edward Elgar Publishing.
Pfau, Johannes, Jan David Smeddinck, and Rainer Malaka, (2020), "Enemy within: Long-term motivation effects of deep player behavior models for dynamic difficulty adjustment. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pp. 1-10.
Popescu, Clara (2020), A guide to cross-promotion: How to increase installs for your mobile game for free. *App/Agent*, April 22, https://www.appagent.co/blog/2020/04/22/a-guide-to-cross-promotion-how-to-increase-installs-for-your-mobile-game-for-free/.
Prins, R., & Verhoef, P. C. (2007). Marketing communication drivers of adoption timing of a new e-service among existing customers. *Journal of Marketing, 71*(2), 169–183.
Rankmyapp (2019), To use or not to use cross promoting strategies for mobile app promotion. April 19, https://www.rankmyapp.com/market/to-use-or-not-to-use-cross-promoting-strategies-for-mobile-app-promotion/.
Reinartz, W., Thomas, J., & Kumar, V. (2005). Balancing acquisition and retention resources to maximize customer profitability. *Journal of Marketing, 69*(1), 63–79.
Rust, R. T., Lemon, K. N., & Zeithaml, V. A. (2004). Return on marketing: Using customer equity to focus marketing strategy. *Journal of Marketing, 68*(1), 109–127.
Sajeesh, S., & Raju, J. S. (2010). Positioning and pricing in a variety-seeking market. *Management Science, 56*(6), 949–961.
Salz, Peggy Anne (2015), Tapdaq empowers app publishers to create community, take charge of user acquisition. *Forbes*, March 24.
Seufert, Eric (2019), How large is the mobile gaming advertising market? *Medium*, https://medium.com/@eric_seufert/how-large-is-the-mobile-gaming-advertising-market-9729e1551a8a.
Sevilla, J., Zhang, J., & Kahn, B. E. (2016). Anticipation of future variety reduces satiation from current experiences. *Journal of Marketing Research, 53*(6), 954–968.
Schmitz, C., Lee, Y.-C., & Lilien, G. L. (2014). Cross-selling performance in complex selling contexts: An examination of supervisory- and compensation-based controls. *Journal of Marketing, 78*(3), 1–19.
SensorTower (2021), "Global app spending approached $65 billion in the first half of 2021, up more than 24% year-over-year. *SensorTower*, June 28, https://sensortower.com/blog/app-revenue-and-downloads-1h-2021.
Shi, Z., Zhang, K., & Srinivasan, K. (2019). Freemium as an optimal strategy for market dominant firms. *Marketing Science, 38*(1), 150–169.
Shin, J., Sudhir, K., & Yoon, D.-H. (2012). When to fire customers: Customer cost-based pricing. *Management Science, 58*(5), 932–947.
Silver, Davis (2020), Top 51 mobile app and gaming statistics 2021. *IronSource*, https://www.is.com/community/blog/top-51-mobile-app-and-gaming-statistics/.
Song, Y., Sahoo, N., & Ofek, E. (2019). When and how to diversify: A multicategory utility model for personalized content recommendation. *Management Science, 65*(8), 3737–3757.
Stephen, A. T., & Toubia, O. (2010). Deriving value from social commerce networks. *Journal of Marketing Research, 47*(2), 215–228.
Subramanian, U., Raju, J. S., & John Zhang, Z. (2014). The strategic value of high-cost customers. *Management Science, 60*(2), 494–507.
Villanueva, J., Yoo, S., & Hanssens, D. M. (2008). The impact of marketing-induced versus word-of-mouth customer acquisition on customer equity growth. *Journal of Marketing Research, 45*(1), 48–59.
Wang, X., & Shankar, V. (2017). Identifying and etimating brand satiation using purchase data: A structural hidden Markov modeling approach. *SSRN*.
Wong, Steven (2016). How Disney Mobile is crossing into the future of entertainment. http://www.alistdaily.com/strategy/disney-mobile-gaming-crosses-future-entertainment/