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Freemium Pricing: Evidence from a Large-scale Field Experiment

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Abstract

Firms commonly run field experiments to improve their freemium pricing schemes. However, they often lack a framework for analysis that goes beyond directly measurable outcomes and focuses on longer term profit. We aim to fill this gap by structuring existing knowledge on freemium pricing into a stylized framework. We apply the proposed framework in the analysis of a field experiment that contrasts three variations of a freemium pricing scheme and comprises about 300,000 users of a software application. Our findings indicate that a reduction of free product features increases conversion as well as viral activity, but reduces usage – which is in line with the framework's predictions. Additional back-of-the-envelope profit estimations suggest that managers were overly optimistic about positive externalities from usage and viral activity in their choice of pricing scheme, leading them to give too much of their product away for free. Our framework and its exemplary application can be a remedy.

Keywords: Freemium, pricing, digitization, experimentation

Electronic copy available at: https://ssrn.com/abstract=2888471

Digital products are characterized by high cost to produce the first copy and very low marginal cost of reproduction (Arrow 1962). This particular cost structure has given rise to freemium pricing — i.e., a hybrid pricing scheme that combines free use of a basic version of the product in perpetuity, with premium upgrades that require the payment of a fee (Anderson 2009; Pauwels and Weiss 2008). Early indications that such pricing strategies are promising were presented by Scott (1976) and more recently by Bawa and Shoemaker (2004).

Freemium pricing is widely adopted by technology companies for their software applications as it allows them to acquire a large number of users at low cost (Lee, Kumar and Gupta 2015). Despite the widespread use of freemium pricing, many firms find it challenging to optimize their respective pricing scheme (Lee, Kumar and Gupta 2015; Pauwels and Weiss 2008). Firms must decide not only what volume of features to give away for free, but also what prices to set for premium upgrades. Further, viral sharing and word-of-mouth are essential to the success of freemium pricing, by fostering adoption with minimal marketing expenditure (Lee, Kumar and Gupta 2015; Oh, Animesh and Pinsonneault 2015; Pauwels and Weiss 2008). The firm must therefore also make decisions about the incentives it sets for users to engage in viral activity (Aral and Walker 2011; Lee, Kumar and Gupta 2015; Trusov, Bucklin and Pauwels 2009). These three decision layers make identification of a profit maximizing pricing scheme complex.

Firms therefore regularly run field experiments (‘A/B tests’) to improve their pricing scheme (Levitt et al. 2016; Seufert 2014; Wedel and Kannan 2016). In evaluating these experiments – due to the aforementioned complexities – managers are rarely guided by an assessment of (multi-period) profit, but mostly base their evaluation on performance indicators that are directly measurable (Seufert 2014). The scientific literature on

freemium pricing is still sparse and offers little guidance on how field experiments can be evaluated with a view towards longer term profit.

Against this backdrop, we structure relevant literature into a stylized framework of freemium pricing, and use the framework to analyze a large-scale field experiment. The randomized experiment comprises close to 300,000 users of a video game for hand-held devices and contrasts three freemium pricing schemes differing in the extent to which product features are given away for free. The experiment shows that a reduction in the amount of free product features increases conversion as well as viral activity, but reduces usage.

Routed in the presented framework, we then perform back-of-the-envelope estimations of the profit impact of the tested pricing schemes. Estimations indicate that managers did not choose the profit-maximizing pricing scheme. The firm preferred higher levels of usage and viral activity over stronger conversion to premium upgrades. Managers anticipated positive externalities from increased usage and viral activity on adoption, serving to reduce customer acquisition cost and increasing possible network effects (Katz and Shapiro 1985). Managers were overly optimistic about the value of these positive externalities. Such excessive optimism and the resulting biased decisions may be common among managers of successful freemium products in growth stages. Our framework and its exemplary application can be a remedy and guide managers towards profit-focused analysis of field experiments.

The remainder of the paper is structured as follows: We first present a stylized framework of freemium pricing that summarizes existing knowledge. We then introduce the field experiment and its observable treatment effects, before thorough outline and discussion of profit estimations. Finally, we briefly conclude.

A Stylized Framework of Freemium Pricing

We structure existing literature into a stylized framework of freemium pricing. The framework, starting from a simple profit function, systematizes parameters that are at the firm's discretion and key value drivers of freemium profit as put forward by scientific and managerial literature. Figure 1 summarizes the framework and first-order effects between key variables, as evidenced in a body of literature (Aral and Walker 2011; Aral, Muchnik and Sundararajan 2009; Bapna and Umyarov 2015; Campbell 2013; Chiou and Tucker 2013; Lambrecht and Misra 2016; Lee, Kumar and Gupta 2015; Liu, Au and Choi 2012; Moe and Fader 2004; Oh, Animesh and Pinsonneault 2015; Pauwels and Weiss 2008; Trusov, Bucklin and Pauwels 2009; Van den Bulte and Joshi 2007; Villanueva, Yoo and Hanssens 2008). The framework will not only serve to derive expectations for experimental outcomes in the next section, but will also form the basis of our profit estimations in the discussion.

[INSERT FIGURE 1 ABOUT HERE]

Profit in Freemium

Freemium pricing refers to perpetually free use of a basic version of a product (a subset of all product features or content) and the offering of premium upgrade options to unlock additional product features, additional content, or an otherwise improved product experience.[1] Users are invited to freely use products or services to generate positive externalities and ad revenue; premium upgrades generate sales revenue. With cost of customer acquisition being the only substantial marginal cost (Lambrecht et al. 2014), firm

profit per customer π can be written as revenue r from premium upgrades (conversion to premium γ times price p) minus customer acquisition cost c_a:

$$(1)\ \pi = r - c_a = \gamma * p - c_a$$

Please note that this formulation pertains to both contractual and non-contractual freemium pricing schemes. In the latter, users can effectuate repeat purchases which will increase p; we assume p to be exogenous to user behavior for simplicity. The formulation further disregards advertising revenue. Advertising-free freemium pricing schemes are broadly adopted in top-grossing products such as Dropbox, Skype and many freemium apps (apps being digitally distributed mobile applications; Sterling 2016). Along these lines, Ghose and Han (2014) analyze a panel of the top 400 ranked apps on Apple's App Store and Google's Play Store, and suggest that including an in-app purchase option is preferable over advertising to monetize freemium apps – which may motivate the choice of many firms not to include advertising in their freemium offering. We disregard advertising revenue in the framework for parsimony and as the product under study did not include advertising at the time of the experiment. Halbheer et al. (2014) and Lambrecht and Misra (2016) present analytical and empirical treatments of ad supported freemium models.[2]

Value Drivers

In improving their offering, firms typically compare different freemium pricing schemes in randomized field experiments, colloquially called 'A/B tests' (Chiou and Tucker 2013; Levitt et al. 2016; Wedel and Kannan 2016). Evaluation of these experiments is mostly informed by directly measurable performance indicators that ultimately determine the profitability of freemium pricing schemes (Seufert 2014). Based

on existing literature (see bottom of Figure 1) we pinpoint three main value drivers that determine the profitability of freemium pricing schemes: Conversion (i.e. premium over all users) γ, usage (intensity/frequency of use) ϑ, viral activity (intensity of users' viral activity) v. These value drivers can be assumed to positively reinforce each other (Lee, Kumar and Gupta 2015; Moe and Fader 2004; Sifa et al. 2015) and relate to profit as follows (Campbell 2013; Liu, Au and Choi 2012; Trusov, Bucklin and Pauwels 2009):

$$(2)\ \pi = \gamma * p - c_a(\vartheta, v)$$

with $\frac{\partial c_a}{\partial \vartheta} < 0$ and $\frac{\partial c_a}{\partial v} < 0$.

Conversion to premium γ. Conversion from free to premium has been found to generate the largest share of revenue in freemium products (Ghose and Han 2014; Sterling 2016). Firms hence aim at high conversion rates. Conversion is commonly measured as the share of premium relative to all users. It tends to be in the single digit percent space of the customer base (Lee, Kumar and Gupta 2015; Maltz and Barney 2012).

Usage ϑ. Usage is important to firms as it is the basis for users' purchases of premium upgrades and as it generates positive externalities. In the case of freemium products distributed via app marketplaces such as Apple's App Store or Google's Play Store, usage is a key determinant of the visibility of an app in the store. Higher visibility increases organic (i.e. without costly advertising) adoption, reducing customer acquisition cost (Liu, Au and Choi 2012). Positive externalities can further arise from network effects if a growing number of users increases the value of the product for other users (Katz and Shapiro 1985). Skype is a good example of how important networks can be for the success of freemium products. The same holds for many social free-to-play games. Usage then is in a positive feedback loop with itself.

Further, more time spent using a freemium product means more time to convert users to premium customers (and more time to expose them to advertising for ad supported freemium products). Sifa et al. (2015) find usage to be an important predictor of freemium purchase decisions. Also, Moe and Fader (2004) find that spending time on a shopping website increases purchase probability. Firms commonly measure usage as the intensity/frequency of product use, e.g. uses per time period.

Viral activity v. Viral activity of existing users is valuable to firms as it attracts new users to the product for free, hence reducing customer acquisition cost (Aral and Walker 2011; Trusov, Bucklin and Pauwels 2009). Lee, Kumar and Gupta (2015) study the incentives set by a provider of online storage to urge users to engage in such viral activity. Viral activity is closely related to and manifests itself as online and offline word-of-mouth. Word-of-mouth has been found to be more efficient than alternative channels of customer acquisition as referred users are characterized by higher viral activity (Trusov, Bucklin and Pauwels 2009) and higher monetary value (Villanueva, Yoo and Hanssens 2008).

Firm Choice

While essential to the firm's evaluation of its freemium pricing scheme, the value drivers of profit that we just presented are not directly set by the firm. The firm rather faces a choice of three parameters that establish the pricing of its freemium offering and related outcomes for the value drivers.

How much to give away for free φ. By definition, freemium pricing allows users to access a subset of a product's content or feature set perpetually for free. Consequently, a

firm has to decide on the amount of free product features/content (relative to all features/content). For simplicity, we will use the terms ‘product features’ and ‘content’ interchangeably. Examples of free content are news articles, songs, movies, TV shows or game levels; examples for free product features are storage space in the case of Dropbox, gameplay features in freemium games, single- versus multi-device use for Spotify or the number of ‘superlikes’ on Tinder. The choice of how much to give away for free can amount to a one-dimensional choice such as the number of freely accessible news articles or the amount of free storage space. For other products, however, the delineation of free versus premium features is a multi-dimensional choice. In gaming applications, for instance, the delineation of free versus premium encompasses the number of levels that are available to players for free, the number of free in-game items that facilitate game play and the placement of paywalls.

Price of premium upgrades p. In addition to delineating free features from premium features, firms have to set a price p for premium upgrades that yield access to more content or product features. In some cases, this decision is equal to setting one global price (for instance, if the payment of a subscription fee allows users to access all premium features, e.g. Lee, Kumar and Gupta 2015; Pauwels and Weiss 2008) but can also amount to setting a bundle of different prices if different premium upgrades are sold separately. Separate sale of premium upgrades is common in video games or phone services. E.g. Skype is selling various premium upgrades including voice mail, own phone number and different calling rates separately.

Viral incentives $\bar{v}$. While the firm cannot directly control the degree of viral activity of a product’s users, it can incentivize viral sharing and word-of-mouth. For

instance, users can be incentivized to send product recommendations or invitations to adopt a product or service to their peers. For example, users of Dropbox obtain an additional 250 megabytes of storage if they successfully invite a friend. Lee, Kumar and Gupta (2015) study these incentives for an online storage provider. Trusov, Bucklin and Pauwels (2009) estimate the upper bound for profitable monetary incentives for a social networking site. The firm can decide on the value of such incentives $\bar{v}$.

Profit Maximization

Optimization Problem. Based on the profit function in equation 1 and 2, the value drivers of profit and the firm's choice set, the firm faces the following problem in its attempt to find a profit-maximizing pricing scheme for its freemium offering:

$$(3)\ \max_{\varphi,p,\bar{v}} \pi = \gamma * p - c_a(\vartheta, v)$$

$$(3')\ \max_{\varphi,p,\bar{v}} \gamma(p, \varphi, \bar{v}) * p - c_a[\vartheta(\varphi, p, \bar{v}), v(\bar{v}, \varphi, p)]$$

$$\text{s.t. } r - c_a > 0$$

For constant prices, revenue is increasing in conversion ($\frac{\partial r}{\partial \gamma} > 0$) and cost of customer acquisition is decreasing in usage ($\frac{\partial c_a}{\partial \vartheta} < 0$; Liu, Au and Choi 2012) and viral activity ($\frac{\partial c_a}{\partial v} < 0$; Trusov, Bucklin and Pauwels 2009). First-order effects of value drivers on profit can hence be summarized as $\frac{\partial \pi}{\partial \gamma} > 0$, $\frac{\partial \pi}{\partial \vartheta} > 0$ and $\frac{\partial \pi}{\partial v} > 0$.

The firm strives for the highest level possible in each of the value drivers. The effect of firm choices on profit however is complex as the three value drivers are not determined independently, but are characterized by multiple trade-offs. For instance, an increase in the amount of features given away for free φ affects firm profits in multiple ways: It generally decreases conversion rate γ (and hence revenues from selling premium features), but increases usage ϑ (which is in turn expected to increase conversion γ) and

lowers cost of customer acquisition c_a (see Figure 1). Similar interdependencies exist for the other two choice parameters (price p and viral mechanisms $\bar{v}$). Generally valid statements about the effect of firm choice on profit are thus impossible. We present further stylized facts summarizing the effects of firm choice on the value drivers of our framework – where generally valid statements are possible.

Effects of free product features. Recent studies (Lambrecht and Misra 2016; Lee, Kumar and Gupta 2015) find that a higher share of free content reduces conversion ($\frac{\partial \gamma}{\partial \varphi} < 0$). Further, the contributions of Oh, Animesh and Pinsonneault (2015) and Chiou and Tucker (2013) suggest that less free content decreases usage, hence $\frac{\partial \vartheta}{\partial \varphi} < 0$. Finally, the effect of an increase in free content on viral activity is moderated by the design of viral mechanisms: If the limitation in free content is strategically used by the firm to set viral incentives (as in the case of free storage space in Lee, Kumar and Gupta 2015), less free content is likely to increase viral activity, in particular electronic word-of-mouth ($\frac{\partial v}{\partial \varphi} < 0$). If the free content itself instigates word-of-mouth as in the case of the New York Times in Oh, Animesh and Pinsonneault's (2015) study, viral activity will increase in the share of free ($\frac{\partial v}{\partial \varphi} > 0$). Summarizing:

> An increase in free product features reduces conversion.
>
> An increase in free product features increases usage.
>
> If the limitation in free product features is used to set viral incentives, more free product features lead to lower viral activity.
>
> If the free product features foster word-of-mouth, a higher share of free product features increases viral activity.

Effects of the price of premium upgrades. The works of Lee, Kumar and Gupta (2015) and Pauwels and Weiss (2008) indicate that, ceteris paribus, a higher price of

premium upgrades reduces both conversion and usage, i.e. $\frac{\partial \vartheta}{\partial \mathrm{p}} < 0$ and $\frac{\partial \gamma}{\partial \mathrm{p}} < 0$. For the ambiguous effects of price on viral activity, the argument is similar to the one for the share of free features above. If premium limitations are used to incentivize users to engage in viral activity, a higher price will make these viral options more attractive which will increase viral activity. Hence:

> An increase in the price of premium upgrades reduces conversion.
>
> An increase in the price of premium upgrades reduces usage.
>
> If the limitation in free features is used to set viral incentives, a higher price for removal of the limitation leads to more viral activity.
>
> If product features foster word-of-mouth, a higher price for removal of the limitation reduces viral activity.

Effects of viral incentives. The firm can set incentives for users to send product recommendations or invitations to peers. The associated incentives are mostly based on rewarding users for exerting influence on peers by granting them access to premium features. Viral incentives can hence act as substitutes for conversion. On the other hand, as viral incentives increase the spread of the product, network effects are likely to be stronger (Katz and Shapiro 1985). Also, Bapna and Umyarov (2015) find strong peer effects in purchase decisions. Hence: $\frac{\partial \vartheta}{\partial \bar{\mathrm{v}}} \lesseqgtr 0$ and $\frac{\partial \gamma}{\partial \bar{\mathrm{v}}} \lesseqgtr 0$. Trusov, Bucklin and Pauwels (2009) and Van den Bulte and Joshi (2007) show that clever design of viral incentives can have strong positive effects on viral activity ($\frac{\partial \mathrm{v}}{\partial \bar{\mathrm{v}}} > 0$). In summary:

> More or stronger viral incentives can increase or decrease conversion.
>
> More or stronger viral incentives can increase or decrease usage.
>
> More and/or stronger viral incentives increase users' viral activities.

The Experiment

The Product

The basis for our experiment is a video game for handheld devices, Jelly Splash, that has been developed and commercialized by the mobile games company Wooga (https://www.wooga.com/games/jelly-splash/, latest visit October 20th 2016). Jelly Splash is distributed as an app on Apple's, Google's, Facebook's and Amazon's respective app marketplaces. It is a casual puzzle game, the most prominent example from this category to date being Candy Crush Saga (Levitt et al. 2016). Across distribution platforms, Jelly Splash has been played by close to 100 million people to date. It makes use of non-contractual freemium pricing with free download and use in perpetuity and in-app purchases to unlock additional content or product features that facilitate gameplay.

In Jelly Splash, players connect lines of at least three adjacent Jellies of the same color to splash them (see figure 2). A level consists of an individually designed board that is randomly filled with Jellies of different colors. Levels are arranged sequentially on a map as can be seen in the left panel of figure 3. Previous levels have to be cleared for a level to be accessible (see figure 3).

Jelly Splash was launched globally at the end of August 2013. Shortly after launch, product managers of Jelly Splash ran their first pricing experiment on Apple's distribution platform, contrasting three different freemium pricing schemes. This experiment is the basis for our study.

Experimental Setup

Gates (AKA Paywalls). After clearing 40 levels, players encounter a 'gate' that needs to be unlocked to access additional levels. This monetization mechanism is equivalent to paywalls which are much used in monetization of information goods (Chiou

and Tucker 2013; Lambrecht and Misra 2016; Oh, Animesh and Pinsonneault 2015). After the initial gate, players encounter additional gates every 20 levels.

Players have three options to unlock gates, as can be seen in the middle panel of figure 3. First, they can unlock the gate with 70 virtual coins that can be purchased for money (one virtual coin costs roughly 1.4 USD-cent). Second, players can engage in viral activity and ask friends on Facebook for keys. To do so, they have to connect the game to their Facebook account which is offered to them shortly after start and repeatedly. This will allow players to send requests from Jelly Splash to their circle of Facebook friends. At least three friends have to respond to the request and send a key to unlock a gate. Sending a key is free to the sender, but requires receivers to have Jelly Splash installed. This is how these game requests foster adoption: If a request is sent to a friend on the social network who has not yet subscribed to Jelly Splash, she has to install the game in order to be able to send a key. Finally, for the third option to unlock a gate, players have to collect a certain number of 'stars'. Stars are obtained by playing levels. A higher score in a level means more stars. Players can collect up to three stars per level (see the indicator bar in the top part of the right panel in figure 2). Levels that have been cleared once can be replayed at any time and in any order which allows players to collect additional stars and unlock a gate without incurring monetary cost or providing their social capital to the company.

[INSERT FIGURES 2 AND 3 ABOUT HERE]

Treatments. The experiment entails three treatments: A baseline condition that exposes players to the default pricing scheme that was implemented before the experiment, and two treatments that presents variations in comparison to the default condition.

The first treatment introduces an additional gate after 20 levels already. Players hence can only play 20 levels for free before encountering a paywall, while they can play 40 levels for free in the default scenario. In terms of the firm's choice variables in our framework, this represents a reduction in free product features.

The second treatment exposes players to the first gate after level 40 as in the default scenario, but the gate can no longer be unlocked with stars (by replaying levels prior to the gate). The rightmost panel of figure 3 presents this gate. About 20% of players have enough stars to unlock the gate after level 40 immediately, affording them with a free unlock. As this free unlock option is taken away, treatment 2, on average, also establishes a reduction in free product features.

Data and Measurement

Data. Data used in our analysis comprises all users that installed Jelly Splash between October 30th and November 4th 2013 globally on an Apple device (both iPhones and iPads) and have played at least one level of Jelly Splash. The experiment ran for 20 days in total. We hence observe behavior of players who installed the game during the five calendar days for 15 days of product use. Afterwards, the firm implemented one of the treatments for all players and behavioral observations would be confounded if the period of observation was extended further.

We cleaned the data for inconsistent entries and apparent technical bugs. The deletion of observations was equally distributed across experimental conditions and leaves us with a sample of 292,293 players. About 15% of users have been randomly allocated to the default pricing scheme. Another 15% have randomly been assigned to treatment 1 and the remaining 70% of users face treatment 2. The relative shares allocated to the different conditions were decided by Wooga.

[INSERT TABLES 1 AND 2 ABOUT HERE]

Descriptive Statistics. We observe several background variables that allow us to assess whether randomization worked appropriately. Table 1 depicts an overview of these background variables. They are largely the same across experimental conditions indicating that users were indeed randomly allocated to the treatments.

The player behavior data made available to us allow us to observe the average snake length that players achieve (i.e. how many Jellies they connect on average) which serves an indicator of player skill. The data further inform us as to the number of stars recorded by players. Table 2 presents summary statistics of pre-treatment user behavior. On average, users accumulated roughly 30 stars in roughly 32 rounds by forming Jelly snakes of an average length of 5.2 Jellies before reaching level 20. Since the three groups have not been treated before level 20, we observe little variation between the groups. We observe minor differences in the conversion rates realized in the different groups (see table 2). In the baseline scenario .65% of all users converted before level 20 while the conversion rate is .71% and .62% of all players in treatment groups 1 and 2 respectively. However, these differences are not statistically significant.[3]

Jelly Splash (similar to most mobile apps) is characterized by a high degree of attrition with only about 44% of players who downloaded the app completing level 20 and 18% completing level 40. Of the 18% that reach the gate at level 40, only about 60% advance to the content beyond. Bear in mind that these numbers reflect the status after 15 days of product use. Over a longer period, a higher share of players can be expected to reach these levels and unlock the gates.

Performance indicators. We want to measure the effect of experimental treatments on value drivers of our framework. We hence match each value driver to a directly observable performance indicator that is commonly used in practice. For conversion, this is the share of premium users, i.e. the number of users who buy a premium upgrade divided by all users. To measure usage, we rely on the number of rounds played by users which is the sum of all attempts (successful or not) to win a level. Finally, viral activity is measured as the number of requests sent from the game to Facebook friends.

Propositions

Both experimental treatments represent a reduction in free product features. Based on the stylized facts of our framework, we hence arrive at the following propositions for experimental effects on performance indicators:

> P1: A reduction in free product features increases the share of premium users (conversion).
>
> P2: A reduction in free product features decreases the average number of rounds played by users (usage).
>
> P3: As the limitation in free product features is used to induce viral spread, a reduction in free product features increases the average number of requests sent by users (viral activity).

Treatment Effects

Table 3 and figure 4 present key results of our experiment. We report average 'intention to treat' effects (Varian, 2016) for users in the different experimental conditions. The impact of experimental treatments on profit will be addressed in the discussion.

[INSERT TABLE 3 AND FIGURE 4 ABOUT HERE]

Treatment 1. Comparing treatment 1 with the default condition identifies the effect of a reduction in free product features (20 free levels instead of 40). While usage (+ .17 %,

p = .85) and conversion (+ 4.29 %, p = .33) remain largely unaffected, viral activity increases substantially (+ 28.08 %, p = .00).[3] These results are in line with the qualitative predictions of our framework and hence substantiate propositions P1, P2 and P3.

The effects on usage and conversion are weak. This can be explained by the fact that approximately 60 % of players reaching the gate after level 20 have already accumulated enough stars to unlock the gate. The gate is hence not binding for most players, i.e. it is already unlocked when they reach it. Nevertheless, this additional gate translates into a valuable increase in viral activity. This outcome speaks to findings of Chiou and Tucker (2013) and Oh, Animesh and Pinsonneault (2015) who find a strong negative effect of paywalls on usage and viral activity. If the paywall is used to induce viral activity and can be easily unlocked, adverse effects may be largely reversed.

Treatment 2. Comparing treatment 2 with the default pricing scheme allows us to identify the effect of another and different reduction in free product features. Usage is clearly reduced (- 7.9 %, p = .00), while conversion (+ 20.98 %, p = .00) and viral activity (+ 15.81 %, p = .00) substantially increase. These results further confirm propositions P1, P2 and P3. More broadly, they confirm that the design of paywalls can strongly impact user behavior (Chiou and Tucker 2013; Lambrecht and Misra 2016).

Additional findings. While auxiliary to the purpose of this study, we wish to briefly comment on the unlock options chosen by users and substitution between them, as observed in the experimental treatments. About 18 % of players reach the gate after level 40 within 15 days of product use in each experimental condition. 11.9 % unlock it within the same time period in the default scenario, 11.6 % in treatment 1 and 12.5 % in treatment 2. With the default pricing scheme, 27 % of users unlocking the gate after level

40 do so by spending money, 37 % unlock it through successful viral activity, and 36 % use stars to unlock the gate. These numbers remain unchanged in treatment 1 where an additional gate after level 20 awaits users. In treatment 2 (where the free unlock option with stars is taken away), 46 % of users unlocking the gate spend money and 54 % use viral activity. Thus, when the free unlock option is removed, more users opt to unlock the gate with money rather than viral activity.

Discussion

We identified the effects of three different freemium pricing schemes on the value drivers of profit (see Table 3 and Figure 4). The stylized facts of our framework (reflected in propositions P1, P2 and P3) were validated in the large-scale field experiment: A reduction in free product features increases conversion as well as viral activity, but reduces usage.

Our findings have broader implications for research on freemium pricing schemes. Most importantly, they relate to the existing literature on the amount of content or features given away for free, and the design of paywalls in particular. First, Oh, Animesh and Pinsonneault (2015) suggest that the existence of a paywall lowers both website traffic and virality. Our findings indicate, however, that paywalls that can be unlocked via referrals can be used as a mechanism to increase viral activity. Moreover, the effect of an additional paywall in our setting only marginally decreases usage while viral activity is strongly increased. The negative effect of an (additional) paywall in our setting therefore seems to be smaller than that of a paywall introduction on news websites as reported in Chiou and Tucker (2013).

Second, the firm ended the experiment after just under three weeks by choosing one of the tested pricing schemes which was then implemented as the default for all new users. We will structure the rest of the discussion around the profit implications of this choice. In particular, we will perform a simple counterfactual profit estimation to showcase how our framework can support firms in focusing their experimental analysis on longer term profit. We further discuss a possible managerial bias that our profit estimates point at.

Managerial Decision and Profit Implications

The pricing scheme underlying treatment 1 leads to the highest viral activity (+ 28.08% compared to pre-experiment pricing scheme, p = .00), while usage is as high as in the default pricing scheme (+ 0.17 %, p = .85). Treatment 2 (i.e. taking away the free unlock option), however, has by far the strongest conversion with 20.94 % (p = .00) more conversions than the default pricing scheme and 15.98 % (p = .00) more than treatment 1 (see Figure 4 and Table 3). At the same time, it also negatively impacts usage compared to the default pricing scheme (- 7.9 %, p = .00), and has lower viral activity than treatment 1's pricing scheme (- 9.58 %, p = .01).

Managers hence faced the trade-off outlined in the introduction: Favor premium conversion (higher immediate revenue and short term profitability), or rather usage and viral activity (higher organic adoption rate which lowers customer acquisition cost and increases longer term profitability)? As, at the time of the experiment, Jelly Splash had only been on the market for two months and was still in a growth stage, managers favored strong viral activity and usage over increased conversion. They opted to implement the pricing scheme underlying treatment 1 for all users, anticipating strong positive externalities (and higher long-term profits) from the higher usage and viral activity.

[INSERT TABLE 4 ABOUT HERE]

At time of writing, Jelly Splash was in a late stage of its product lifecycle – paid marketing activity was halted and new user influx is very low. This allows for a 'lifetime' perspective on the game and its users, in the sense that at this late stage in the product lifecycle, long-run users and profits have been largely realized. Positive externalities from usage and viral activity have in large part materialized and can be quantified as overall adoption that was not directly induced by marketing, but through usage and the viral activity of users acquired through marketing. In this section, we will make use of this additional information to perform a back-of-the-envelope counterfactual estimation of the profit that would have resulted for each pricing scheme respectively. We will first describe the additional 'lifetime' data, then outline the assumptions and calculations underlying the estimations, and finally present results.

'Lifetime' data. Additional data that were made available to us by Wooga describe the behavioral outcomes of users who were exposed to the pricing scheme underlying treatment 1 for their whole lifetime of product use. We know the lifetime share of premium users (conversion), average lifetime rounds played (usage) and average lifetime requests sent (viral activity) of users in treatment 1. Additionally, Wooga informed us on all-time marketing spend, adoption induced by marketing (which is the number of users that downloaded the game app following exposure to an ad; as attributed by Wooga's business intelligence system), and total adoption of the game.

Assumptions and profit estimation. Denoting overall marketing spend by C_a, total adoption by N, lifetime share of premium users by γ and average price paid per premium user by p, we can calculate profit per user based on the simple function from equation 1 of our framework:

$$(4)\ \pi = \gamma * p - \frac{C_a}{N}$$

Total adoption N consists of marketing induced adoption N_{mktg} (as attributed by Wooga's business intelligence system) and non-marketing induced adoption $N_{non\text{-}mktg}$; hence: $c_a = \frac{C_a}{N} = \frac{C_a}{N_{mktg}+N_{non-mktg}}$.

Assuming that all non-marketing induced adoption $N_{non\text{-}mktg}$ results from usage ϑ and viral activity v of users acquired through marketing (driving down customer acquisition cost as depicted in Figure 1), we can further write:

$$(5)\ N_{non\text{-}mktg} = f(\vartheta,v) = e_{usage} * \vartheta + e_{viral} * v$$

where e_{usage} and e_{viral} are the positive externalities of usage and viral activity on adoption. They measure adoption per unit of usage and viral activity respectively. This step is essential for linking our framework to real-world scenarios faced by managers. The assumed linearity of externalities is simplistic but serves as a conservative test, given that a concave relationship would be more plausible. Overall, we choose our assumptions to maximize chances that the managerial assessment and decision result in highest estimated profit—i.e., that Wooga's managers were 'correct'.

Further, by assuming that organic (non-marketing induced) adoption results in equal parts from usage and the viral activity of users acquired through paid marketing, we can estimate the positive externalities as follows: $e_{usage} = \frac{0.5*N_{non-mktg}}{N_{mktg}*\vartheta}$ and $e_{viral} = \frac{0.5*N_{non-mktg}}{N_{mktg}*v}$. This assumption that usage and viral activity each cause one half of organic adoption of the product is admittedly rather strong. However, the key result of our profit

estimations is robust to different specifications of this assumption – we return to this issue later.

We need additional assumptions to estimate profit outcomes for the other two experimental conditions. Denoting experimental conditions by index i:

- The positive externalities from usage and viral activity are equally strong in the different pricing schemes: $e_{usage,i}=\bar{e}_{usage}$ and $e_{viral,i}=\bar{e}_{viral}$
- Marketing spend and effectiveness are exogenous: $C_{a,i} = \bar{C}_a$ and $N_{mktg,i} = \bar{N}_{mktg}$
- Differences in user behavior at the end of the experiment are indicative of lifetime differences. This assumption is strong, but sensible as differences between experimental conditions converge over the period of observation.

In line with equation 4, this allows us to calculate profit in each treatment as:

$$(4') \ \pi_i = \gamma_i * \bar{p} - \frac{\bar{C}_a}{\bar{N}_{mktg}+N_{non-mktg,i}}$$

Where:

$$(5') \ N_{non\text{-}mktg,i} = \bar{e}_{usage} * \vartheta_i + \bar{e}_{viral} * v_i$$

Profit per experimental condition. Table 4 depicts the profit estimates resulting from the above assumptions, and calculations as percentages of the default pricing scheme. We cannot state actual numbers for confidentiality reasons. The pricing scheme tested in treatment 1 is estimated to increase profit compared to the default pricing by roughly 15 %, the one underlying treatment 2 by roughly 40 %. Treatment 1 has higher viral activity and higher usage than treatment 2, but substantially lower conversion (see Table 3). This results in the lowest estimated customer acquisition cost for treatment 1's pricing scheme and highest estimated revenue for treatment 2's (see Table 4) – which is sensible.

Per our interviews, managers chose the pricing scheme of treatment 1 because it displayed highest usage and viral activity, anticipating strong positive externalities from both. Ex post, however, this choice was not profit maximizing as Wooga could have generated higher revenues by allowing for higher investments in paid marketing. While this drives up customer acquisition cost, it would have led to higher profit (see Table 4).

Robustness checks. Our profit estimations required strong assumptions. Even though we chose assumptions conservatively, we wish to address explicitly whether relaxing them may change our conclusion about the profit-maximizing pricing scheme.

The ranking of pricing schemes by resulting profit is stable across reasonable levels of positive externalities from usage and viral activity (figure A1 in the appendix depicts the ranking in more detail). Even if each additional round played and each additional request sent would have resulted in adoption of the game by one additional user, the pricing scheme of treatment 2 would still result in the highest profit. In fact, the outperformance of the pricing scheme tested in treatment 2 over the firm's choice is roughly constant for different levels of externality from viral activity, and increases in the externality from usage.

The profit ranking of the pricing schemes is further constant for different attributions of non-marketing induced adoption to usage and viral activity (i.e., relaxing our earlier assumption about equal attribution). More generally, it should be noted that we chose assumptions that are as favorable as possible for the positive externalities from usage and viral activity. In reality, usage and viral activity will not cause organic (non-marketing induced) adoption alone, but there will be a baseline of user influx from other sources, such as 'random' discovery on the app marketplaces and mentions in press articles. The key result of our profit estimations that the higher usage and viral activity

under treatment 1 cannot result in more profit than the higher conversion under treatment 2 is robust to virtually all reasonable specifications of our assumptions.

Possible antecedents of the managerial decision. At time of the experiment, managers would have needed to additionally assume/estimate values for the lifetime variables that we introduced above, but – using the presented framework and adopting the back-of-the-envelope profit estimations – they could have had a strong indication that the pricing scheme underlying treatment 1 cannot result in higher profits than that of treatment 2. Implementing treatment 2's pricing scheme would hence have been the (locally) optimal choice, also at time of the managerial decision. Managers' choice of treatment 1 can only be explained by strong optimism about the positive externalities from usage and viral activity (we intentionally do not call it 'irrational' as there may be other behavioral benefits to this kind of optimism; Weinstein and Klein 1996; Hilary et al. 2016).

Such managerial optimism and resulting biases have long been studied in economics (De Meza and Southey 1996; Kahneman, Slovic and Tversky 2013) and management research (Hilary et al. 2016; Ucbasaran et al. 2010). After investing a lot of time and effort into product development, managers want to see the product being used as much as possible by as many people as possible (leading them to favor low customer acquisition cost over higher revenue). Additionally, with the firm belief that their product is the best, managers may anticipate unrealistically strong positive externalities from usage and viral activity. Both their optimism about the product and the externalities it can produce lead managers to make biased decisions that do not result in the highest profit for the firm: They give too much of their freemium product away for free.

Limitations and Future Research

Our stylized framework builds on first derivatives and does not account for non-linear relationships and second order effects. For some of the effects, (inverse) U-shaped relationships may be more appropriate characterizations. For the amount of free features for example, we posit a negative association to conversion. It is however likely that this association is positive up to a certain point (where customers get hooked) and negative beyond that. While conversion may decrease in additional free features in most observed settings, this may be an incomplete account of the two parameters' full relationship.

Further, while we checked the robustness of our results, we only present plain intention-to-treat effects (Varian 2016). Heterogeneous treatment effects, while not helpful for the purposes of the present study, are an interesting avenue for further research. Lambrecht and Misra (2016) start exploring in this direction by distinguishing customers' reaction to a paywall by their valuation of the offered content. We consider customer learning to be an important angle. Learning appears to be strong in freemium environments where customers often fail to have a priori price beliefs and form habits while using the free version of the product. A more comprehensive account of such dynamics and customer heterogeneity is a highly relevant avenue for future research. Lee, Kumar and Gupta (2015) start investigating this avenue by presenting a dynamic model of customer behavior based on micro foundations.

Finally, our profit estimations require strong assumptions. While we confirmed that they are in line with managerial reasoning and the resulting insights are highly valuable, it should be noted that they are indicative and by no means conclusive. It will be interesting to see if the discussed optimism bias can be found among managers of freemium products and startups more broadly.

Conclusion

While firms commonly run field experiments to improve their freemium pricing schemes, they often lack a framework for comprehensive and profit-focused analysis. Against this backdrop, we present a framework that systematizes key parameters governing freemium pricing and summarizes relevant stylized facts. We apply this framework in analysis of a field experiment comprising close to 300,000 users of a software application. The experiment contrasts three different freemium pricing schemes in a video game for handheld devices. We find that a reduction in free product features increases conversion rates and viral activities, and reduces usage – which is in line with the stylized facts of our framework.

The presented framework, combined with strong (yet conservative) assumptions, further allows us to perform a back-of-the-envelope counterfactual profit estimation. We estimate the profit that would have resulted if each of the pricing schemes tested in the experiment had been implemented for all users respectively. Estimates indicate that managers did not make a profit maximizing decision at the end of the experiment. The firm would likely have been better off generating higher revenue and investing the additional profit into paid marketing.

We discuss possible antecedents of the managerial decision that may be common among managers of successful freemium products in a growth stage: After investing a lot of time and effort into product development, managers want to see their product being used as much as possible by as many people as possible. They favor lower customer acquisition cost over higher revenue and are overly optimistic about the positive externalities the product can generate, leading them to give too much of their product away for free. Our framework and its exemplary application can be a remedy.

References

Anderson, Chris (2009), *Free: the future of a radical price.* New York: Hyperion.

Aral, Sinan, Lev Muchnik, and Arun Sundararajan (2009), "Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks," *Proceedings of the National Academy of Sciences* 106, 21544–21549.

Aral, Sinan, and Dylan Walker (2011), "Creating Social Contagion Through Viral Product Design: A Randomized Trial of Peer Influence in Networks," *Management Science* 57, 1623–1639.

Arrow, Kenneth (1962), "Economic Welfare and the Allocation of Resources for Invention," in *The Rate and Direction of Inventive Activity*, Richard Nelson, ed. Princeton: Princeton University Press.

Bapna, Ravi, and Akhmed Umyarov (2015), "Do Your Online Friends Make You Pay? A Randomized Field Experiment on Peer Influence in Online Social Networks," *Management Science* 61, 1902–1920.

Bawa, Kapil, and Robert Shoemaker (2004), "The Effects of Free Sample Promotions on Incremental Brand Sales," *Marketing Science* 23, 345–363.

Campbell, Arthur (2013), "Word-of-Mouth Communication and Percolation in Social Networks," *American Economic Review* 103, 2466–2498.

Chiou, Lesley, and Catherine Tucker (2013), “Paywalls and the demand for news,” *Information Economics and Policy* 25, 61–69.

De Meza, David, and Clive Southey (1996), “The Borrower’s Curse: Optimism, Finance and Entrepreneurship,” *The Economic Journal* 106, 375–386.

Dunnett, Charles W. (1955), “A Multiple Comparison Procedure for Comparing Several Treatments with a Control,” *Journal of the American Statistical Association* 50, 1096–1121.

Fisher, Ronald Aylmer (1970), *Statistical methods for research workers*. Edinburgh: Oliver and Boyd.

Ghose, Anindya, and Sang Pil Han (2014), “Estimating Demand for Mobile Applications in the New Economy,” *Management Science* 60, 1470–1488.

Halbheer, Daniel, Florian Stahl, Oded Koenigsberg, and Donald R. Lehmann (2014), “Choosing a digital content strategy: How much should be free?,” *International Journal of Research in Marketing* 31, 192–206.

Hilary, Gilles, Charles Hsu, Benjamin Segal, and Rencheng Wang (2016), “The bright side of managerial over-optimism,” *Journal of Accounting and Economics* 62(1), 46–64.

Kahneman, Daniel, Paul Slovic, and Amos Tversky (1982), *Judgment under uncertainty: Heuristics and biases*. Cambridge: Cambridge University Press.

Katz, Michael L., and Carl Shapiro (1985), "Network Externalities, Competition, and Compatibility," *The American Economic Review* 75, 424–440.

Kim, Ju-Young, Martin Natter, and Martin Spann (2009), "Pay What You Want: A New Participative Pricing Mechanism," *Journal of Marketing* 73, 44–58.

Lambrecht, Anja, Avi Goldfarb, Alessandro Bonatti, Anindya Ghose, Daniel G. Goldstein, Randall Lewis, Anita Rao, Navdeep Sahni, and Song Yao (2014), "How do firms make money selling digital goods online?" *Marketing Letters* 25, 331–341.

Lambrecht, Anja, and Kanishka Misra (2016), "Fee or Free: When Should Firms Charge for Online Content?" *Management Science*.

Lee, Clarence, Vineet Kumar, and Sunil Gupta (2015), "Designing Freemium: Balancing Growth and Monetization Strategies," Working Paper (accessed November 2, 2015), [available at https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=2767135].

Levitt, Steven D., John A. List, Susanne Neckermann, and David Nelson (2016), "Quantity discounts on a virtual good: The results of a massive pricing experiment at King Digital Entertainment," *Proceedings of the National Academy of Sciences* 113, 7323–7328.

Liu, Charles Z., Yoris A. Au, and Hoon Sek Choi (2012), “An empirical study of the freemium strategy for mobile apps: Evidence from the Google Play Market,” *Proceedings of the 2012 International Conference on Information Systems*.

Maltz, Jules, and Daniel Barney (2012), “Should Your Startup Go Freemium?” (accessed March 20, 2015), [available at http://www.techcrunch.com].

Moe, Wendy W., and Peter S. Fader (2004), “Dynamic Conversion Behavior at E-Commerce Sites,” *Management Science* 50, 326–335.

Oh, Hyelim, Animesh Animesh, and Alain Pinsonneault (2015), “Free vs. For a Fee: The Impact of Information Pricing Strategy on the Pattern and Effectiveness of Word-of-Mouth via Social Media,” *MIS Quarterly* 40, 31–56.

Pauwels, Koen, and Allen Weiss (2008), “Moving from Free to Fee: How Online Firms Market to Change Their Business Model Successfully,” *Journal of Marketing* 72, 14–31.

Schmidt, Klaus M., Martin Spann, and Robert Zeithammer (2015), “Pay What You Want as a Marketing Strategy in Monopolistic and Competitive Markets,” *Management Science* 61, 1217–1236.

Scott, Carol A. (1976), “The Effects of Trial and Incentives on Repeat Purchase Behavior,” *Journal of Marketing Research* 13, 263.

Seufert, Eric Benjamin (2014), *Freemium economics: leveraging analytics and user segmentation to drive revenue*. Amsterdam, Boston: Elsevier/Morgan Kaufmann.

Sifa, Rafet, Fabian Hadiji, Julian Runge, Anders Drachen, Kristian Kersting, and Christian Bauckhage (2015), "Predicting Purchase Decisions in Mobile Free-to-Play Games," *Eleventh Artificial Intelligence and Interactive Digital Entertainment Conference*.

Sterling, Greg (2016), "In-app purchases dwarf ad revenues, as iOS App Store exceeds $71 billion," (accessed on May 25, 2016), [available at http://www.marketingland.com].

Trusov, Michael, Randolph E. Bucklin, and Koen Pauwels (2009), "Effects of Word-of-Mouth Versus Traditional Marketing: Findings from an Internet Social Networking Site," *Journal of Marketing* 73, 90–102.

Tukey, John W. (1949), "Comparing Individual Means in the Analysis of Variance," *Biometrics* 5, 99.

Ucbasaran, Deniz, Paul Westhead, Mike Wright, and Manuel Flores (2010), "The nature of entrepreneurial experience, business failure and comparative optimism," *Journal of Business Venturing* 25(6), 541–555.

Van den Bulte, Christophe, and Yogesh V. Joshi (2007), "New Product Diffusion with Influentials and Imitators," *Marketing Science* 26, 400–421.

Varian, Hal R. (2016), “Causal inference in economics and marketing,” *Proceedings of the National Academy of Sciences* 113, 7310–7315.

Villanueva, Julian, Shijin Yoo, and Dominique M. Hanssens (2008), “The Impact of Marketing-Induced Versus Word-of-Mouth Customer Acquisition on Customer Equity Growth,” *Journal of Marketing Research* 45, 48–59.

Wedel, Michel, and P.K. Kannan (2016), “Marketing Analytics for Data-Rich Environments,” *Journal of Marketing* 80, 97–121.

Weinstein, Neil D., and William M. Klein (1996), “Unrealistic Optimism: Present and Future,” *Journal of Social and Clinical Psychology* 15, 1–8.

Yates, F. (1934), “Contingency Tables Involving Small Numbers and the Chi-square Test,” Supplement to the *Journal of the Royal Statistical Society* 1, 217.

Footnotes

1) An additional perspective on freemium pricing locates it between (but not including) free-trial pricing where free product use eventually comes to an end, and pay-what-you-want pricing where customers have full access to the product and are free in their choice to spend money (Kim, Natter and Spann 2009; Schmidt, Spann and Zeithammer 2015).

2) Advertising revenues could be included in our framework in a rather straightforward manner. The degree of advertising exposure would be an additional choice variable for the firm and ad revenues an additional outcome variable that serves to increase revenue.

3) As our samples are very large and asymptotic properties apply, we rely on parametric tests of statistical significance. We ran analyses-of-variance (Fisher 1970) with a Tukey post-hoc test (Tukey 1949) for the metrically scaled variables (rounds played, requests sent). As this test procedure assumes equal variances between samples (the empirically observed variances differ weakly as sample sizes differ between experimental conditions), we ran independent samples t-tests allowing for unequal variances to corroborate results. For the nominally scaled variable share of premium users, we used Chi-square tests (Yates 1934). In the text, we report average effect sizes and the *p*-values of t-test and Chi-square test. The multiple treatment comparison can be accommodated with a Bonferroni adjustment (Dunnett 1955).

Tables

TABLE 1: DESCRIPTIVES FOR BACKGROUND VARIABLES

Variable	**Description**	**Default Scenario**	**Treatment 1**	**Treatment 2**	**Total**
N	Sample size	43,660	43,218	205,415	292,293
GDP 2013	GDP of country that game was installed from, $	41,603/43,033 (900/140644)	41,535/43,033 (696/140644)	41,577/43,033 (696/140644)	41,575/43,033 (696/140644)
Device age	Time since release of user's device, in months	23.6/25 (0/53)	23.7/25 (0/53)	23.6/25 (0/53)	23.6/25 (0/53)
Tablet	Game was played on an iPad (dummy)	.3163/0 (0/1)	3139/0 (0/1)	.3125/0 (0/1)	.3133/0 (0/1)
iOS7	User had upgraded to iOS7 (dummy)	.7764/1 (0/1)	.7794/1 (0/1)	.7789/1 (0/1)	.7786/1 (0/1)
US	Game download in the United States (dummy)	.3251/0 (0/1)	.3249/0 (0/1)	.3257/0 (0/1)	.3255/0 (0/1)
GB	Game download in Great Britain (dummy)	.2151/0 (0/1)	.2170/0 (0/1)	.2139/0 (0/1)	.2146/0 (0/1)
FR	Game download in France (dummy)	.066/0 (0/1)	.0641/0 (0/1)	.0661/0 (0/1)	.0658/0 (0/1)
Social network	User connected to Facebook (dummy)	.1971/0 (0/1)	.2058/0 (0/1)	.2066/0 (0/1)	.2050/0 (0/1)
Total friends	Facebook friends of the user	304.8/200 (0/4726)	308.7/200 (0/4676)	308.3/205 (0/4871)	307.9/203 (0/4871)

Notes: Showing M/median (min/max) for each entry

TABLE 2: PRE-TREATMENT DESCRIPTIVES FOR OUTCOME VARIABLES

Variable	**Base Scenario**	**Treatment 1**	**Treatment 2**	**Total**
Rounds played	32.017/28 (1/732)	31.6022/28 (1/1019)	31.4871/27 (1/1068)	31.5833/28 (1/1068)
Conversion	.0065/0 (0/1)	.0061/0 (0/1)	.0071/0 (0/1)	.0068/0 (0/1)
Ask requests sent	1.198/0 (0/716)	1.1908/0 (0/708)	1.2163/0 (0/980)	1.2098/0 (0/980)
Give requests sent	.1841/0 (0/41)	.1855/0 (0/44)	.1907/0 (0/93)	.1889/0 (0/93)
Stars collected	29.5445/34 (0/57)	29.4375/33 (0/57)	29.4272/34 (0/57)	29.4462/34 (0/57)
Average snake length	5.2339/5.1429 (.8889/11)	5.2368/5.1429 (.5556/11)	5.2334/5.14 (.2941/11.6667)	5.2339/5.1429 (.2941/11.6667)

Notes: Showing M/median (min/max) for each entry

TABLE 3: OUTCOME VARIABLES AT THE END OF THE EXPERIMENT

Outcome variable	**Base Scenario**	**Treatment 1**	**Treatment 2**	**Total**
	N = 43,660	N = 43,218	N = 205,415	N = 292,293
Usage				
Rounds played	83.2736/40 (1/1837)	83.4142/39 (1/1281)	76.6969/39 (1/2401)	78.6725/39 (1/2401)
Conversion				
Share of premium users	.0234/0 (0/1)	.0244/0 (0/1)	.0283/0 (0/1)	.027/0 (0/1)
Viral activity				
Requests sent	7.5561/0 (0/3095)	9.6778/0 (0/5493)	8.751/0 (0/7936)	8.7096/0 (0/7936)
Additional variables				
Stars collected	44.1855/35 (0/364)	44.0331/35 (0/266)	42.9535/35 (0/530)	43.2972/35 (0/530)
Average snake length	5.202/5.1081 (.8889/11)	5.2089/5.1154 (.5556/11)	5.1942/5.0896 (.2941/11.6667)	5.1975/5.0952 (.2941/11.667)

Notes: Showing M/median (min/max) for each entry

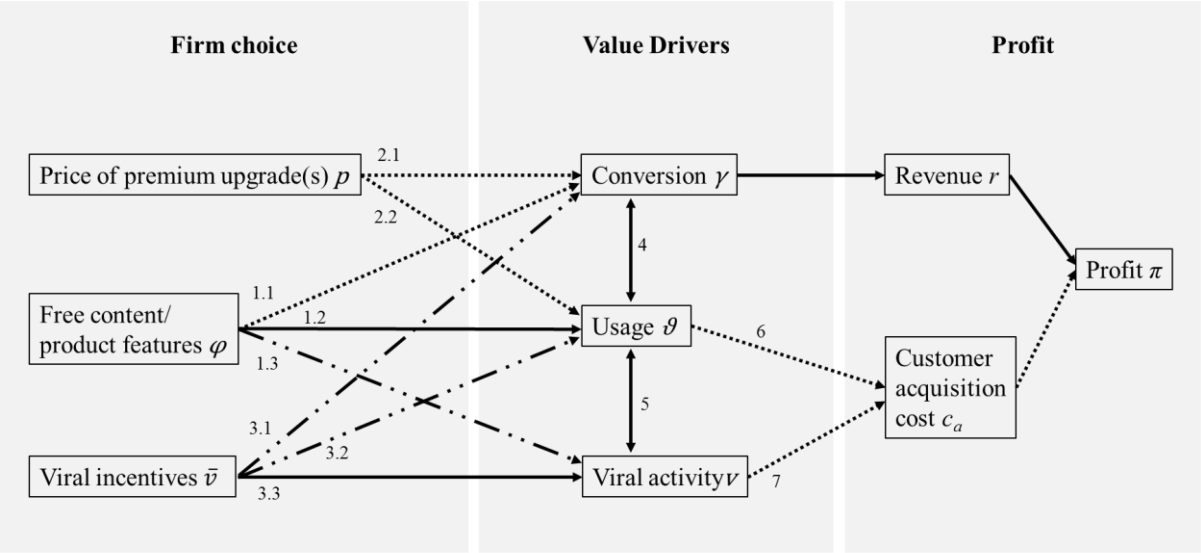
TABLE 4: PROFIT ESTIMATES PER PRICING SCHEME

	Treatment 1 (Firm choice)	**Treatment 2 (Highest profit)**
Profit	***116%***	***142%***
Revenue	***104%***	***121%***
Conversion	104%	121%
Price (constant)	100%	100%
Customer acquisition cost	***92%***	***98%***
Marketing spend [a]	100%	100%
Marketing-induced adoption [a]	100%	100%
Externality-induced adoption	112%	103%
Usage (lifetime rounds played)	100%	92%
Usage externality (adoption per round played) [a]	100%	100%
Viral activity (lifetime sent requests)	128%	116%
Viral externality (adoption per sent request) [a]	100%	100%

Notes: We cannot state actuals for confidentiality reasons; values given as percent of the respective outcome in the default pricing scheme; a – assumed to be constant between pricing schemes; the discussion details the assumptions and calculations underlying the estimates.

Figures

FIGURE 1: A STYLIZED FRAMEWORK OF FREEMIUM PRICING



1.1 Lambrecht and Misra (2016)
Lee, Kumar and Gupta (2015)
1.2 Oh, Animesh and Pinsonneault (2015)
Chiou and Tucker (2013)
1.3 Lee, Kumar and Gupta (2015)
Oh, Animesh and Pinsonneault (2015)
2.1 Pauwels and Weiss (2008)
2.2 Lee, Kumar and Gupta (2015)

3.1 Bapna and Umyarov (2015)
Villanueva, Yoo and Hanssens (2008)
Aral, Muchnik and Sundararajan (2009)
Katz and Shapiro (1985)
3.2 Pauwels and Weiss (2008)
Aral, Muchnik and Sundararajan (2009)
Van den Bulte and Joshi (2007)
3.3 Trusov, Bucklin and Pauwels (2009)
Aral and Walker (2011)

4 Moe and Fader (2004)
Sifa et al. (2015)
5 Trusov, Bucklin and Pauwels (2009)
6 Campbell (2013)
Liu, Au and Choi (2012)
Trusov, Bucklin and Pauwels
7 (2009)
Aral, Muchnik and Sundararajan (2009)
Villanueva, Yoo and Hanssens (2008)

Positive effect
Negative effect
Ambiguous/moderated effect

FIGURE 2: SCREENSHOTS OF JELLY SPLASH AND ITS KEY GAME MECHANIC

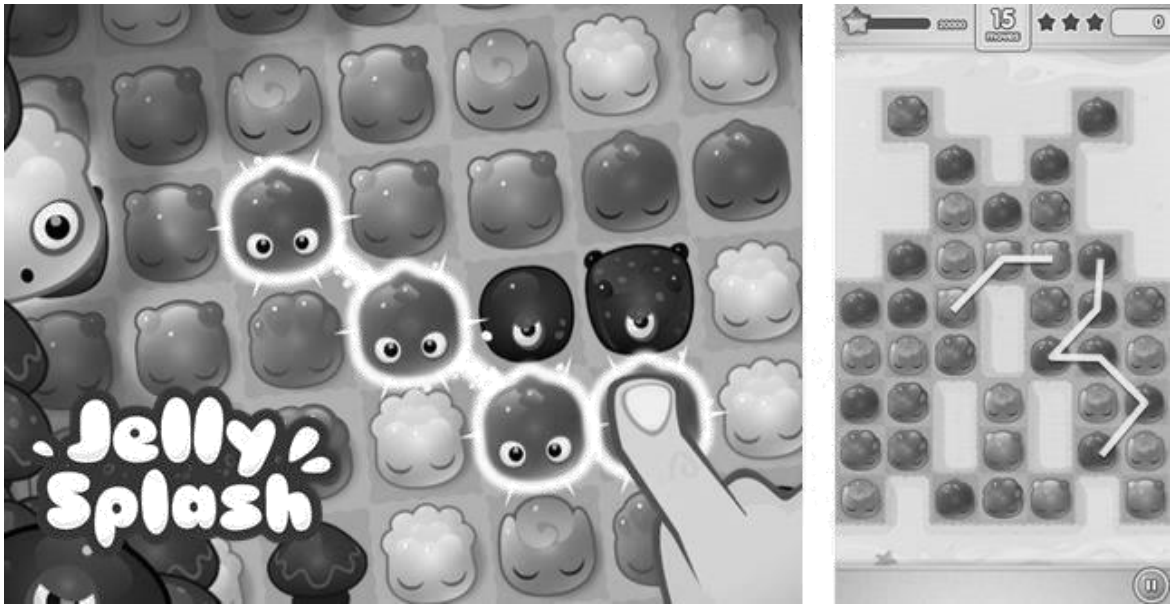
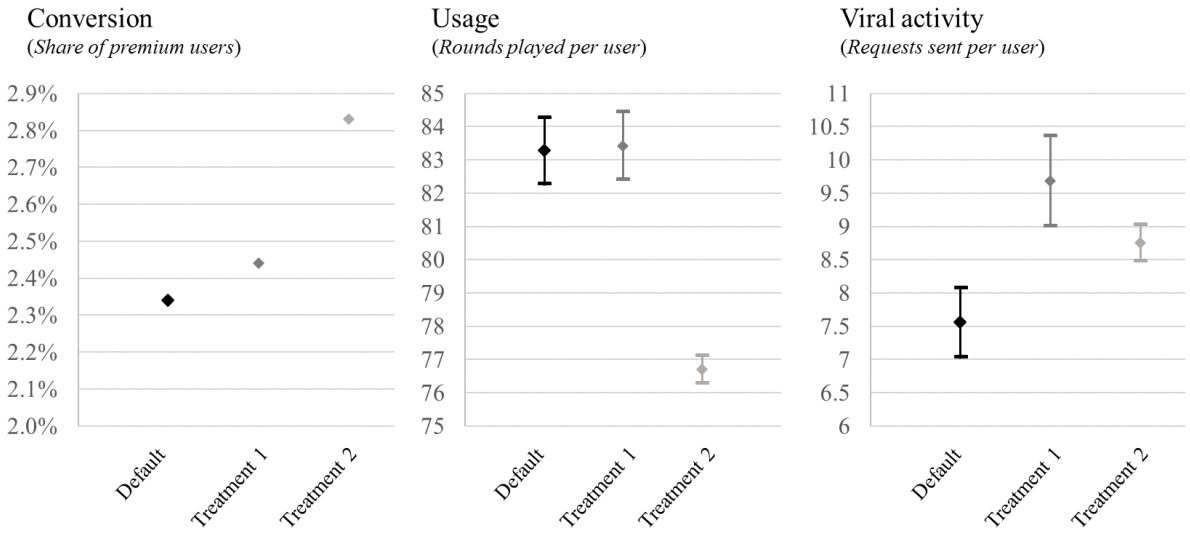


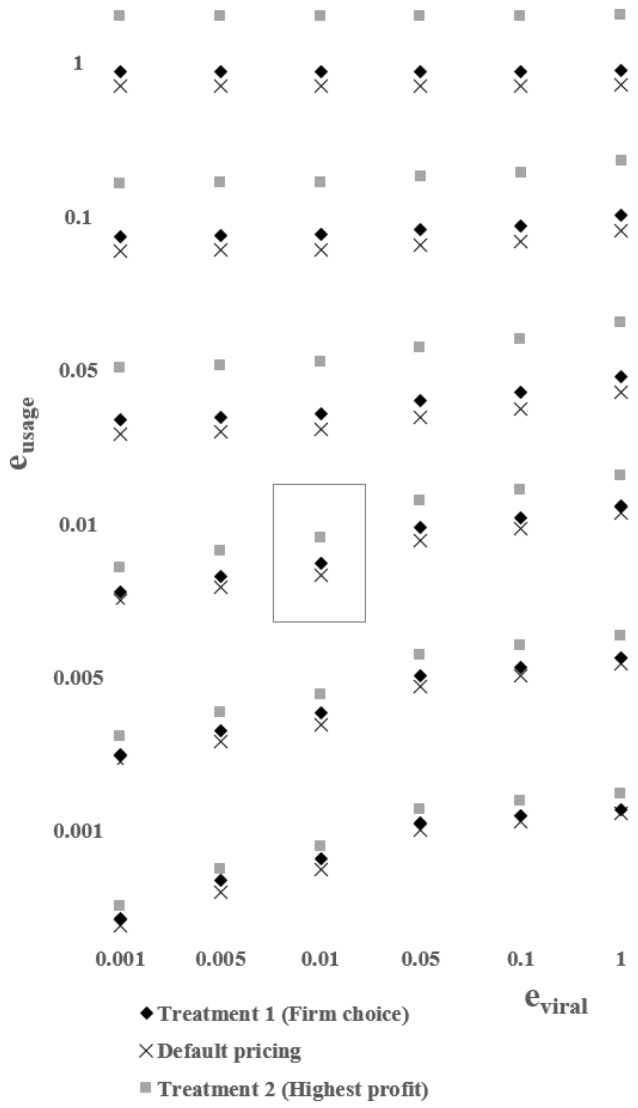
FIGURE 3: JELLY SPLASH MAP AND GATES

FIGURE 4: EFFECTS OF TREATMENTS ON VALUE DRIVERS



Appendix

FIGURE A1: PROFIT ESTIMATES FOR DIFFERENT LEVELS OF EXTERNALITIES



Notes: Externality from usage denoted as e_{usage} and externality from viral activity as e_{viral}; the externalities that were observed in the data are indicated by a grey rectangle.

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