THE IMPACT OF INNOVATION AND SOCIAL INTERACTIONS ON PRODUCT USAGE

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Abstract

We investigate the motivations behind product usage in categories characterized by frequent product updates and social interactions between users. The proposed approach builds on theoretical work on experiential products to define consumer utility as a function of intrinsic preferences, social interactions, the match of content with user experience, and future benefits. We empirically test our model using a novel individual data set from the online gaming industry on daily content consumption, product innovation, and group membership. The results show that usage of simpler features is primarily motivated by intrinsic preferences, while group interactions and future benefits of learning about the product are relatively more important to explain consumption of more complex content. We find that an early innovation schedule and lowering content complexity can motivate engagement in initial stages of the product lifecycle, while providing incentives to social interactions is useful to increase content consumption in later stages.

Keywords: product usage, dynamic demand models, forward-looking consumers, online content, experiential products.

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1 Introduction

Activity consumption is a significant component of the U.S. economy, with approximately \$25.1 billion spent on video games, consoles, and accessories (Entertainment Software Association 2011) and \$30 billion on crafts and hobbies in 2010 (Craft and Hobby Association, 2011; Luo, Ratchford, and Yang, 2013). In terms of digital and online consumption, the numbers are also noteworthy. Individuals can now access software, games, and social communities through smartphones, computers, and their gaming consoles (Williams, Yee, and Caplan, 2008), and according to Nielsen, 81 billion minutes were spent on social networks and blogs in 2011 and 42% of tablet owners use them daily while watching TV (Nielsen, 2011). Closely related to the empirical application in this paper, the worldwide market for online games surpassed \$15 billion in 2010 with additional sales of virtual goods likely to exceed \$1 billion (Playlogic Entertainment Inc, 2010). With online connectivity and the presence of the Internet, online or network games have been growing exponentially, with a recent study showing that about 67% of teenagers regularly play some game online (Playlogic Entertainment Inc, 2010).

Although product usage and content consumption are ubiquitous consumer decisions and largely explain repeat-purchase or product replacement (Huh and Kim, 2008), past marketing literature has focused on the adoption or purchase stage (e.g., Mahajan, Muller, and Bass, 1990 and 1995; Rogers, 2003). Ultimately, the products purchased by consumers lead to consumption activities or product usage, such as playing games and sports, eating and drinking, watching TV, taking pictures, or recording movies (Luo, Ratchford, and Yang, 2013), but research on post-purchase behavior and product usage has been limited because of the lack of revealed preferences data on consumption; data collection mostly focuses on transactional information. As an alternative, until recently, surveys or self-reported questionnaires have been used to study usage behavior, especially regarding technology products (Ram and Jung, 1990; Shih and Venkatesh, 2004; Huh and Kim, 2008).

To completely understand the interaction of consumers and products, post-purchase behavior and product usage need to be carefully examined, and more research is required to fully understand the drivers of product consumption and its impact on long-term consumer engagement with the product (Golder and Tellis, 2004; Shih and Venkatesh, 2004).[1] The main objective of this paper is to fill this gap in the marketing literature by proposing a model of product usage that measures the importance of the main drivers behind use of a product, in this case an online game, and investigate how a firm can influence usage patterns through innovation or facilitating social interactions. To illustrate our approach, we make use of a unique data set - from the popular online video game World of Warcraft - that tracks product usage, content consumption choices, and social interaction decisions by more than 200 individuals over two years, at a daily level, during which the firm introduced multiple product updates. Our empirical application highlights the importance of consumer past usage and expertise, and social interactions as motivations of product usage, while being able to quantify the impact of product updates to a firm interested in keeping consumers involved with the product. To the best of our knowledge, this is one of the first empirical studies to examine how different usage drivers specified by theoretical work influence consumption decisions using revealed-preferences data on product usage.

Our research builds on two streams of literature. The first stream is based on psychological or sociological theories that study consumption or usage choices. The motivations for product usage and consumption were developed in the seminal papers by Holbrook and Hirschman (Holbrook and Hirschman, 1982; Hirschman and Holbrook, 1982). The subsequent literature that developed this theoretical work primarily used qualitative approaches to examine the different needs that are satisfied by engaging in a given activity or consumption (e.g., Ajzen and Driver 1992; Celsi, Rose, and Leigh 1993; Holbrook et al. 1984; Holt 1995). According to this research, consumer interest and enjoyment depend not only on tangible product characteristics, but also on intangible benefits, such as the sociability of actions or the satisfaction arising from consumption of previously unexplored content (Holbrook and Hirschman, 1982; Unger and Kernan, 1983). This literature serves as basis to the choice of components of the consumer utility function that explain product usage decisions in our model.

[1] An anecdotal example of how important the relation between the purchase (subscription) decision and product usage is to managers and consumers alike was provided in May of 2011 at the earnings call of Activision Blizzard, one of the major developers of computer games. At the call, the discussion revolved around one of their main products, the popular online game *World of Warcraft,* which contributed a large percentage of the firm's profits. Subscriptions declined from 12 million paying customers at the end of 2010 to 11.4 million at the end of March of 2011 and continued to rapidly drop until May. In response to questions about this decline, the company's CEO, Mike Morhaime, said that "subscriber base does not change linearly. It fluctuates based on content consumption, which players seem to be doing a whole lot of – at a more rapid pace", and continued by promising "faster release of new content" to respond to the demand decline.

The second stream of research includes quantitative methods that explore the relation between consumer consumption, past individual decisions, and future outcomes. For example, using purchase data that mimics usage patterns closely, Hartmann and Viard (2008) and Koppalle et al. (2012) propose dynamic methods that investigate the effect of rewards on consumer activity in the golf and hotel industries as a function of effort accumulated to the decision date, explaining changes in the frequency of product usage as consumers get closer to rewards. Expanding these studies to a broader perspective, Luo, Ratchford, and Yang (2013) use leisure activities data to investigate the relation between consumption usage decisions and consumer lifestyles. The authors' premise is that consumption of a subset of activities is defined by what consumers have learned in the past and their expertise, resulting in a set of repeated activities that define a lifestyle.

Papers that relate product usage with innovation and changes in available consumption options are sparse. A recent example by Huang, Khwaja and Sudhir (2012) studies the consumption decisions of drinks using intra-day data, with consumers deciding between managing short run needs (e.g., hydration and mood pickup) with long-term goals (e.g., health). Although these authors use their model to evaluate the introduction of new products, innovation is not part of their original setting. Our paper contributes to both aforementioned literature streams by developing a model of consumer usage decisions and studying two theoretically relevant factors that explain consumption that have been mostly ignored before in empirical studies: the sociability of actions and introduction of new content for consumption.

Our empirical application illustrates several interesting substantive findings. First, we show that motivations for product usage vary for different content choices. For more basic content, intrinsic preferences for the product dominate the decisions, while for more complex content, social interactions and future benefits resulting from gains in expertise become increasingly important. Second, in terms of innovation, we show that the timing of product updates drives significant use of the product, but with primarily impact on a small segment of early users that are also skilled. For other segments, postponement of new content launch is almost irrelevant. Third, we show that there is a trade-off between content complexity and innovation speed. While we find that it is beneficial for the firm to lower content complexity to increase early and broader engagement with the product, this may create the need for more frequent product updates. Finally, using our model, we are able to quantify the impact of incentives to social interactions, which are found to lead to longer engagement with the product, especially in later stages of the product lifecycle.

The remainder of the paper is structured as follows. The next section describes the model. Section 3 provides details about the novel data set on post-purchase decisions used in the paper. The estimation algorithm and a discussion about identification are presented in Section 4. The results and managerial implications are described in Section 5, and Section 6 concludes.

2 A Model of Product Usage in the Presence of Innovation and Sociability of Actions

We develop a model of consumer choices about product usage and content consumption in environments characterized by the introduction of product updates and sociability of actions. We start by outlining our model framework and defining the per-period utility from choices. Next, we specify the forward-looking behavior of consumers by elaborating on the relevant state variables and consumer expectations. We end this section by combining the per-period utility with the continuation value of future periods to obtain the decision-making utility that explains consumer decisions.

2.1 Framework

We model product usage decisions in a social environment where consumers have the possibility of enjoying the product individually or with a community of other users. Every period t, consumer i makes two decisions in sequence indexed by d: first, she chooses whether she should be a member of a user group (stage $d = 1$); second, she decides on content consumption (stage $d = 2$). These two decisions are interrelated because social interactions may affect the enjoyment of content consumption; also, consumer preferences when using the product are likely to influence the decision to be part of a community.

In order to join a community, a consumer goes through a costly process of selecting a group of other consumers with whom to use the product. Once part of a group, the user obtains a number of benefits, including the opportunity to socialize with other individuals who have similar interests and collaborate on content consumption. Conditional on the decision to be part of a community of users, individuals choose from the available consumption alternatives, $j = 0, ..., J_t$, where $j = 0$ is the outside alternative of not using the product. The alternatives represent different types of content associated with the product or different ways in which a consumer can use a product. Each product update p ($p = 1, ..., P$) launched by the firm adds content choices, and therefore the number of choice alternatives J_t becomes larger with innovation. When needed, we use subscript p for alternative j to indicate which product update introduced content j in the market.

Consumers gain expertise with usage, which impacts future interactions with the product, for example, by making it easier to use advanced features. Consumers anticipate the gains of experience obtained with usage and also the launch of new content. This is true in many consumption environments. For example, in video games, product updates are common and demand expertise from users to enjoy newly introduced content. In television series, consumers decide to watch an episode partially because of instantaneous utility and partially because that decision allows them to enjoy future episodes. Hence, we assume that consumers are forward-looking when making decisions and take into account future utility in their community membership and content consumption choices.

2.2 Per-period Utility of Social Interaction

Consumer communities, defined as networks of users or admirers of a brand, influence consumer perceptions of products (Algesheimer, Dholakia, and Herrmann, 2005; Muniz and Schau, 2005), with user interactions and social motivations explaining much of the variation in purchase choices and consumer behavior (e.g., Arndt, 1967; Bonfield, 1974). Examples of groups include users signing up to participate in a discussion forum about content, a Facebook group about a product, or a guild or clan of players in a video game, as it is the case in our application.

At each time t, consumer i decides on their status regarding communities of users of the product: she can join a group, remain in a group if already part of one, leave that group, or remain without any connections to user communities.[2] We assume that consumers can make this decision at any

[2] We opt to model the consumer decision to join any group, instead of a specific group, in part due to data limitations and what can be identified in the empirical application. The model could be made to accommodate the consumer decision of choosing a specific group by changing the choice set at this decision stage and adding elements to the utility such as group characteristics.

time t and denote the outcome of a community decision as m_{it}:

$$m_{it}|m_{i,t-1} = \begin{cases} 1|m_{i,t-1} = 0, & \textit{join group} \\ 1|m_{i,t-1} = 1, & \textit{remain in group} \\ 0|m_{i,t-1} = 0, & \textit{remain with no group} \\ 0|m_{i,t-1} = 1, & \textit{leave group} \end{cases} . \tag{1}$$

The term $m_{i,t-1}$ is the social interaction decision in period $t-1$ and therefore denotes the membership state for individual i at the beginning of period t. We assume that the social interaction decisions provide the following per-period utility, conditional on the membership state:

$$u_{imt}|m_{i,t-1} = \begin{cases} k_{imt} + r_{imt} + \varepsilon_{imt}, & if\ m_{it} = 1|m_{i,t-1} = 0 \\ r_{imt} + \varepsilon_{imt}, & if\ m_{it} = 1|m_{i,t-1} = 1 \\ \varepsilon_{imt}, & otherwise \end{cases} . \tag{2}$$

If the consumer does not belong to the community at period t but decides to join (i.e., $m_{it} = 1|m_{i,t-1} = 0$), she pays a one-time joining cost k_{imt}. These costs are likely to depend on the relative level of user experience at time t. Relatively more experienced consumers can help others, making them valuable to a community and more sought after. Consequently, we expect them to have lower joining costs than less experienced consumers. Formally, we define the joining cost function as follows:

$$k_{imt}(l_{it}, \bar{l}_t) = \begin{cases} \kappa_1 + \kappa_2 I(l_{it} > \bar{l}_t), & if \quad m_{it} = 1 \ and \ m_{i,t-1} = 0, \\ 0, & otherwise, \end{cases} \tag{3}$$

where l_{it} denotes user i's experience and $\bar{l}_t$ stands for the average experience across all users at time t.

As long as the consumer is part of the community, she enjoys membership benefits denoted by r_{imt}. These benefits include socializing with others or the sense of prestige from being a member of a network of users and can be enjoyed separately from content consumption. The utility derived from those benefits is also likely to be influenced by the relative experience of consumers. We define it as:

$$r_m(l_{it}, \bar{l}_t) = \begin{cases} \lambda_1 + \lambda_2 I(l_{it} > \bar{l}_t), & if \quad m_{it} = 1, \ \forall m_{i,t-1}, \\ 0, & otherwise. \end{cases} \tag{4}$$

We standardize the deterministic per-period utility of remaining outside of communities to zero, for identification purposes. Finally, we assume that there is an unobserved (to the researcher) component of the per-period utility of social interaction, ε_{imt}, which is independently and identically distributed across time and individuals and follows a Type I extreme value distribution.

2.3 Per-period Utility of Content Consumption

Once the community decision is made, consumers decide on which content to enjoy - or which product features to use - from a set J_t available at time t. New content or additional product features are launched by the firm through product updates indexed by p that expand the choice set for consumers. The per-period utility for individual i of consuming content alternative j_p at time t is given by

$$u_{ij_pt} = \underbrace{\alpha_{0i} + \alpha_{1ij} + \alpha_{2i}X_t}_{\substack{Intrinsic \\ Preferences}} + \underbrace{f\left(a_{i,t-1}, \tau_{pt}\right)}_{\substack{Content \\ Aging/Novelty}} + \underbrace{g\left(l_j, l_{it}\right)}_{\substack{Content \\ Match}} + \underbrace{h\left(l_i, \bar{l}_t\right)}_{\substack{Competitive \\ Effect}} + \varepsilon_{ijt}. \tag{5}$$

The utility function has four components based on literature about product usage. We model intrinsic preferences using a heterogeneous intercept α_{0i}, a heterogeneous and content-specific intercept α_{1ij}, and observed variables X_t. The first two components account for both individual-specific preferences for functional benefits and subjective experiential enjoyment from consumption, such as fun and excitement of consuming content (Hirschman and Holbrook, 1982; Holbrook and Hirschman, 1982). The variables X_t include dummies for the days of the week, and hence the term $\alpha_{2i}X_t$ accounts for differences in preferences for when to use the product.

The second component in the utility function focuses on the time variation of content appeal. Previous literature has found that the utility from content consumption may vary over time, for reasons such as product aging or consumer satiation (Coombs and Avrunin, 1977). For example, when consumers are satiated with a product, they may prefer an alternative with different attributes on the next purchase occasion (Lattin and McAlister 1985; McAlister 1982). In addition, the appeal of novel content is expected to decrease with aging, with consumers likely to prefer to experience something new (Berlyne 1970; Raju 1984). The effect of novelty and product aging is modeled as a function of two components, past consumption actions and time since content launch:

$$f(a_{it-1}, \tau_{pt}) = \mu_i a^0_{i,t-1} + \beta_{1ip}\tau_{pt} + \beta_{2ip}\tau^2_{pt}. \tag{6}$$

The term, $\mu_i a^0_{i,t-1}$, measures the impact of consumer i having consumed any type of content recently, in our case, in the previous time period, with $a^0_{i,t-1}$ taking the value of 1 if the consumers engaged with the product in period $t-1$. A negative estimate for μ_i would reveal the presence of satiation with the product, while a positive value would reveal habit formation (e.g., Pollak, 1970; Spinnewyn, 1981). The second component relates to content age, captured by the number of days τ_{pt} since the product update p was introduced in the market. With the development of other products and technology, product aging and features introduced by different updates are likely to lose appeal over time, even in the absence of product usage. Previous research has shown that the pattern of enjoyment in products that are experienced repeatedly over time is one that usually begins at a low level, increases progressively with time, peaks, and then gradually subsides (Hirschman and Holbrook, 1982). Accordingly, we account for the possibility of non-linear aging effects using the quadratic function.[3]

The third term accounts for the match between consumer ability and complexity of content. The available content may require different levels of ability, experience, and knowledge about product features, and typically consumers gain expertise while using a product (Luo, Ratchford, and Yang, 2013). Early theoretical frameworks modeled the influence of consumer expertise on tastes and choices because consumers tend to avoid consumption possibilities outside the range of their past consumption experiences (e.g., Pollak, 1970; Spinnewyn, 1981). To capture these aspects, we assign each content alternative with a level of complexity l_j, and each consumer with expertise level l_{it}.

The level of content difficulty l_j is assumed to be observed and known by consumers. With l_j in hand, we define the individual experience level l_{it} as an observed consumer state that takes

[3] It is possible to also include a more permanent satiation directly dependent on product usage, but we found that the one-day state dependence combined with content aging to explain the data well.

the value of the highest level of any content enjoyed before time t by individual i.[4] The utility of each task j is influenced by the match of the complexity level of content and the level of consumer expertise. With this in mind, we define the content match term as

$$g\left(l_j, l_{it}\right) = \begin{cases} \gamma_{1i}\left(l_{it} - l_j\right), & if \quad l_{it} > l_j \\ \gamma_{2i}\left(l_j - l_{it}\right), & if \quad l_{it} \leq l_j \end{cases}. \tag{7}$$

In practice, this approach places each content choice on a ladder position l_j, and consumers shift positions over time endogenously through consumption decisions, moving their expertise level closer to more challenging content as they use the product. We expect that alternatives with a complexity level that neighbors the level of the user to be more enjoyable (Pollak, 1970; Spinnewyn, 1981) and both coefficients γ_{1i} and γ_{2i} to be negative.

The fourth and final component involves a competitive effect, when consumers compare their performance with the performance of other consumers. When product usage is visible to others or related experiences are shared, users likely care about their status. We model this status effect by comparing individual i's level l_{it} and the mean level of other consumers at time t, $\bar{l}_t$, and define it as

$$h\left(\bar{l}_t, l_{it}\right) = \begin{cases} \delta_i, & if \quad l_{it} \geq \bar{l}_t \\ 0, & otherwise \end{cases}. \tag{8}$$

The impact on utility from being above and below the mean expertise level of the user population can be interpreted as "snob" and "bandwagon" effects, based on the literature on prestige-seeking behavior (e.g., Leibenstein, 1950; Vigneron and Johnson, 1999). The "snob", or social prestige effect, makes consumers want to be exclusive, different, and to dissociate themselves from the "common herd," while the "bandwagon" effect captures the desire to conform with others in order to be fashionable or stylish (Leibenstein, 1950). Hence, a positive value of δ_i is evidence of the "snob" or prestige effect, while a negative value of δ_i is a sign of a "bandwagon" behavior.

[4] Although it is possible to have a more complex function for consumer expertise that accounts for both the quantity and level of past content consumed, we find that the maximum level of past content complexity matches a wide range of applications. For example, in computer games, a player's level is usually defined as a function of most complex completed content; in TV series, viewership of the latest episode shown is also a good representation of the most useful knowledge about the storyline events. In other applications, that might not be true. For example, in educational products, the amount and level of content absorbed are both important to measure consumer progression in learning. In that case, a more complex expertise function is necessary. We note that both l_{it} and l_t are discretized for the estimation algorithm.

Finally, we assume that ε_{ijt} are unobserved shocks that are independently and identically distributed across individuals, time, and content, and follow a Type I extreme value distribution. For identification purposes, the deterministic part of the per-period utility of choosing the outside alternative - not consuming any content - is fixed at zero.

2.4 State Transitions and Consumer Beliefs

The consumer state at time period t and decision stage d - community membership $d = 1$ or content choice $d = 2$ - is described by: 1) the community membership status, $m_{i,t-1}$; 2) the individual experience level, l_{it}; 3) the index of the most recent content batch $\tilde{p}_t$, which defines the choice set available to consumers; 4) the number of time periods since the introduction of product update p, τ_{pt}; 5) the competitive position $\tilde{l}_{it} = I(l_{it} \geq \bar{l}_t)$; 6) the most recent content usage choice, $a^0_{i,t-1}$; and 7) any other time-specific effects, X_t. We collect these state variables into the vector $S^d_{it} = \left\{m_{i,t-1}, l_{it}, \tilde{p}_t, \tau_{pt}, \tilde{l}_{it}, a^0_{i,t-1}, X_t\right\}$.

In each time period t, a consumer starts by making her social interaction choice in stage $d = 1$, hence updating her community membership state $m_{i,t-1}$, and then proceeds to content decision $d = 2$. The state variable l_{it} evolves when individual i chooses content of a higher level of complexity than her current experience level l_{it} and succeeds at completing it. Otherwise, this state variable does not take on a new value. Progression in experience is not always guaranteed for highly complex content. For examples, in our application, users of a video game can choose content that is hard to complete and have to repeat it in some cases multiple times before proceeding with the game storyline. The success rate for task j is denoted by w_{ijt} and depends on inherent individual-specific ability, the experience level of the user, the difficulty of the content, and guild membership status. Therefore, consumer expectations regarding their experience level at $t + 1$ are given by

$$l_{i,t+1} = \begin{cases} l_j \; with \; probability \; w_{ijt}, & if \; l_j > l_{it}, \\ l_{it}, & otherwise, \end{cases} \tag{9}$$

where w_{ijt} is an entry in the matrix of success rates W_{it}. We provide more details about W_{it} in the data section.

The state variable $\tilde{p}_t$ denotes the index of the most recently introduced product update, $\tilde{p}_t \in$

$\{0, ..., P\}$. Consumers are uncertain about the timing of new content release but have rational expectations based on known previous schedules of content introductions. To represent these expectations, we estimate the probability of an update launch by specifying a parametric discrete time duration model and using historic data on update releases. The probability of an update occurrence - and hence the transition probability for $\tilde{\rho}$ - after $\tau_{\tilde{p}t}$ time periods since the introduction of the previous update $\tilde{p}$ is defined as

$$Pr(\tilde{p}_{t+1} = \tilde{p}_t + 1 | \tau_{\tilde{p}t}) = 1 / \left(1 + e^{-\left(\chi_1 + \chi_2 \tau_{\tilde{\rho}t}\right)}\right), \tag{10}$$

where χ_1 and χ_2 are estimated parameters.[5] We assume that users know the number of updates that a firm is going to launch, for example based on historic innovation patterns by the firm as in our application, and that after the introduction of the last update, consumers do not expect any more updates.

A consumer is aware that her current choice of content can change her competitive position in the next time period. Consumers develop rational expectations about their own expertise level $l_{i,t+1}$ being above or below the average experience level $\bar{l}_{t+1}$ of the user population. Those expectations depend on own content choice and the likelihood of its successful completion, as well as other relevant information: the age of the most recent content (the community level is likely to change less for older content) and consumer current competitive position. We specify consumer expectations for their competitive position in the user population, $\tilde{l}_{i,t+1} = I(l_{i,t+1} \geq \bar{l}_{t+1})$, as

$$Pr\left[\tilde{l}_{i,t+1} = 1\right] = w_{ijt} \times \left[1 / \left(1 + e^{-(\boldsymbol{\omega} \boldsymbol{Y}_t)}\right)\right], \tag{11}$$

where $\tilde{l}_{i,t+1} = 1$ indicates that consumer's expertise level is above the population average in period

[5] The probability $Pr(\tilde{p}_{t+1} = \tilde{p}_t + 1 | \tau_{\tilde{p}t})$ reflects the firm's propensity to invest in resources to generate more content. From the consumer's point of view, this propensity is assumed to be exogenous; each individual consumer believes that her actions will not influence the firm's decision and timing of product updates. In our application, the firm appears to have invested a certain amount of resources in the product (e.g., hired programmers) to support a fairly stable schedule of content introduction; according to announcements from the firm, new content is launched whenever ready and stable for usage, not before and not after. This decision resulted in several updates in the first half of the product lifecycle, followed by a longer period of time without additional introductions before the next version of the product. A similar schedule had also happened before our analysis period and supports the assumption that the schedule of product updates is an exogenous decision by the firm and not directly influenced by a consumer's usage decisions. In addition, in our application, the transition to a new product update can occur only on Tuesdays, when server maintenance is performed, which makes $Pr(\tilde{p}_{t+1} = \tilde{p}_t + 1 | \tau_{\tilde{p}t}, \boldsymbol{X}_t) = 0$ except when $X_t^{Monday} = 1$. For the estimation of the duration model, $\tau_{\tilde{p}t}$ is measured in weeks. The model was estimated by maximum likelihood and the estimated parameters with standard errors in parenthesis are: $\chi_1 = -2.885$ (0.738) and $\chi_2 = 0.228$ (0.126).

$t+1$, the vector $\boldsymbol{Y}_t$ captures the expectation-relevant information, and vector $\boldsymbol{\omega}$ are estimated parameters.[6]

Finally, the time effects X_t, the most recent chosen content $a^0_{i,t-1}$, and the age of the product updates τ_{pt} evolve deterministically.[7] Consumer beliefs about all aforementioned future states are represented by Markov transition probability functions denoted by $\pi(S^{d=2}_{it}|a^{d=1}_{it}, S^{d=1}_{it})$ and $\pi(S^{d=1}_{i,t+1}|a^{d=2}_{it}, S^{d=2}_{it})$, where a^d_{it} denotes the consumer choice for the remainder of the paper.

We end this section by discussing the consumer knowledge of the quantity and quality of content of future product updates. Matching the setting of our application, we assume that consumers know ahead of time the number and quality of content to be introduced in the future. We find this assumption reasonable because we focus on experienced users and content had frequently been introduced for several years before the period analyzed in our study, providing enough information to predict characteristics of future innovation.[8]

2.5 Consumer Choices

A consumer has preferences defined over a sequence of states from period t to period T, with time horizon T being finite or infinite. Using the per-period utility function defined earlier, we represent these preferences at the start of time t by the discounted utility stream

$$E\left(\sum_{k=0}^{T-t}\rho^k\left[\sum_{d=1}^{2}u\left(a^d_{it+k}, S^d_{it+k}\right)\right]\right), \tag{12}$$

where ρ is a time discount factor such that $\rho \in (0,1)$, $u\left(a^d_{it+k}, S^d_{it+k}\right)$ is the per-period utility function for decision d conditional on consumer state vector S^d_{it+k}, and the expectation is taken over future

[6]Given that w_{ijt} are known, we estimate the vector of parameters $\boldsymbol{\omega}$ using a logit model, where the dependent variable is the competitive position in period $t+1$ and independent variables represent expectation relevant information available to consumer in period t that we collect in vector $\boldsymbol{Y}_t$. The estimates for the intercept, current level of expertise, age of content, and update-specifc effects, and current competitive position, with standard errors in parenthesis, are: $\omega_0 = -33.998$ (0.809), $w_{max(a,l)} = 2.311$ (0.061), $\omega_{\tilde{p}\,age} = -1.825$ (0.052), $\omega_{p=1} = 22.743$ (0.623), $\omega_{p=2} = 19.787$ (0.567), $\omega_{p=3} = 13.002$ (0.432), $\omega_{\tilde{l}} = 9.402$ (0.099).

[7]We estimated our model using both finite and infinite horizons, and the results do not change significantly between these two cases. Our results are based on the infinite horizon formulation. Since we use the infinite horizon approach, we need to cap the time variable for content aging. We choose a large number - 210 days - from the introduction of an update, after which the content does not age.

[8]Our model can be applied even when consumers are unsure about the number of product updates, but the expectations about this quantity would need to be formulated.

states with uncertainty and utility shocks.[9] There is no time discounting between decisions $d = 1$ and $d = 2$ at each time period, since they immediately follow each other within t.

The consumer maximizes her discounted utility stream by making choices a_{it}^d that affect her state. Therefore, Equation 12 is a dynamic programming problem for consumer i. Let $V\left(S_{it}^d\right)$ be the value function of being in state S_{it}^d:

$$V\left(S_{it}^d\right) \equiv \max_{a_{it}^d} E\left(\sum_{d'=d}^{2} u\left(a_{it}^{d'}, S_{it}^{d'}\right) + \sum_{k=1}^{T-t} \rho^k \left[\sum_{d=1}^{2} u\left(a_{it+k}^d, S_{it+k}^d\right)\right]\right). \tag{13}$$

By definition, the value function $V\left(S_{it}^d\right)$ represents the maximum discounted utility stream that a consumer can obtain by starting in decision stage d of time period t and behaving optimally from that point forward, given his state S_{it}^d.

Consumers know that they make two decisions in period t and reason recursively. The last decision to be made in period t is the choice of content, $d = 2$. The consumer realizes that her content choice not only brings immediate utility, $u\left(a_{it}^2, S_{it}^2\right)$, but also influences her utility from period $t + 1$ forward, as measured by Equation 13. Using the Bellman principle of optimality, we write down the consumer choice-specific value function in decision stage $d = 2$ as:

$$v(a_{it}^{d=2}, S_{it}^{d=2}) \equiv u\left(a_{it}^{d=2}, S_{it}^{d=2}\right) + \rho \int_S V(S_{it+1}^{d=1}) d\pi(S_{it+1}^{d=1} | a_{it}^{d=2}, S_{it}^{d=2}). \tag{14}$$

Moving backwards to decision stage $d = 1$, the choice-specific value function at the stage of the community membership choice is

$$v(a_{it}^{d=1}, S_{it}^{d=1}) \equiv u\left(a_{it}^{d=1}, S_{it}^{d=1}\right) + \int_S V(S_{it}^{d=2}) d\pi(S_{it}^{d=2} | a_{it}^{d=1}, S_{it}^{d=1}). \tag{15}$$

The maximum value across all possible choices in period t in stage d is described in Equation 13. Therefore, $V(S_{it}^d) = \max\limits_{a \in A_{it}^d} \left\{v(a, S_{it}^d)\right\}$, and we represent the value functions for stages $d = 1$ and

[9] In our application, we set the time discount rate to 0.975 per day, which corresponds to 0.84 per week. This time discount rate is in line with values used in the literature on entertainment and experiential products. For example, Hartmann and Viard (2008) use a similar value, while Ishihara and Ching (2012) estimates a discount rate of 0.885 per week for video games. See Yao et al. (2011) for a list of other discount rates choices. We tested other discount rates and got similar substantive results.

$d = 2$ recursively as follows:

$$V(S_{it}^{d=2}) = \max_{a \in A_{it}^{d=2}} \left\{ u\left(a, S_{it}^{d=2}\right) + \rho \int_S V(S_{it+1}^{d=1}) d\pi(S_{it+1}^{d=1} | a, S_{it}^{d=2}) \right\}, \tag{16}$$

$$V(S_{it}^{d=1}) = \max_{a \in A_{it}^{d=1}} \left\{ u\left(a, S_{it}^{d=1}\right) + \int_S V(S_{it}^{d=2}) d\pi(S_{it}^{d=2} | a, S_{it}^{d=1}) \right\}. \tag{17}$$

Equations 16 and 17 are referred to as Bellman equations, and we discuss the solution to this system of functional equations in Section 4.2.

The consumer choice-specific value function can be decomposed as $v\left(a_{it}^d, S_{it}^d\right) = \overline{v}\left(a_{it}^d, S_{it}^d\right) + \varepsilon_{iat}$, where ε_{iat} is an i.i.d. Type I extreme value random shock to consumer's per-period utility of each decision (ε_{ijt} and ε_{imt}). Using the properties of the extreme value distribution, we can write the probability that consumer i chooses action a in stage d of time period t, conditional on his state vector S_{it}^d, as follows:

$$Pr(a | S_{it}^d) = \frac{exp\Big(\overline{v}\left(a, S_{it}^d\right)\Big)}{\sum\limits_{b \epsilon A_{it}^d} exp\left(\overline{v}\left(b, S_{it}^d\right)\right)}. \tag{18}$$

These individual choice probabilities are used in the estimation routine to obtain the parameters of the utility function.

3 Industry and Data

The proposed approach can be used to obtain insights about the relation between product usage, sociability of actions, and innovation in a number of industries. We demonstrate its application with the study of consumer demand in the online computer gaming industry.

3.1 An Online Game

We use data from the online game *World of Warcraft* developed by Blizzard Entertainment, a division of Activision Blizzard. According to the game's website, *World of Warcraft* is a "Massively Multiplayer Online Role-Playing Game (MMORPG), set in the high-fantasy universe centered around persistent online personae."[10] In other words, the game involves virtual characters with which in-

[10]For more information, visit http://us.battle.net/wow/en/.

dividuals explore the environment developed by programmers. The game was originally introduced in 2004 and became the best-selling PC game of 2005 and 2006 worldwide. By 2011, Blizzard had launched three full-fledged expansions and dozens of patches that added new content. The three expansions introduced large quantities of new content and in most cases a new chapter in the storyline behind the game, with patches either modifying previous versions of the game or introducing smaller amounts of content. In 2008, the game had more than 11.5 million subscribers worldwide. Our data is related to the second expansion of the game, which sold more than 4 million copies in the first month alone (Blizzard Entertainment, 2008).

The game environment and related data are particularly suitable to the study of product usage for a number of reasons. First, users enjoy a storyline by repeatedly making consumption choices of content. Through these choices, they progress deeper into the storyline and enjoy an expanding number of features and content, which makes experience and forward-looking behavior essential components. Second, most user actions are visible to others since players interact in the shared environment and individuals have the opportunity to join online communities to share experiences, and explore content simultaneously. These attributes add a unique social dimension to product usage.

Blizzard Entertainment releases detailed statistics about player participation and performance to provide a more complete experience to users and allow them to track their progress in the game. These data take the form of dates of first-time completion of specific content consumption or a task performed in the game. Several independent websites process this information into databases that allow cross-player comparisons and provide recommendations on how to progress in the game. In this paper, we use a publicly available data set on product usage collected from such a site called *Wowhead*.[11] We complement these data with information about product updates, their content, firm's actions, and other announcements from the official game website.

Although purchase decisions are not the focus of the paper, we emphasize that the pricing scheme used by the firm creates a strong link between payments and product usage. The firm charges a fixed price for the initial game and each major expansion, but the majority of revenues comes from additional fees paid by users to access the online game server and consumer content. The subscription price per day ranges from about 40 to 50 cents per day, depending on the payment plan,

[11] Available at www.wowhead.com.

and all product updates are free once consumers have subscribed to the game with no additional purchase decisions at the time of introduction of product updates. This allows us to focus on usage-related decisions and abstract from price response.

3.2 Choice Sets and Product Updates

Our data set includes daily information about the game from November of 2008 to December of 2010. This time period covers the entire lifecycle of the second game expansion from its launch date until the introduction of the third expansion. The expansion includes three product updates that added content available to players. To account for different initial conditions and skill of each player, we use the beginning periods in our data set to create a starting state for each player, which includes their level in the game, an innate skill level, the membership status in a game community, and whether he or she played the game recently. We use 163 time periods for initialization, leaving 607 periods for analysis.

Statistics about the choice sets at the introductory time period and for additional patches are presented in Table 1. The firm usually starts by launching more content to provide a detailed background to a storyline. Once the background is set, the firm introduces a lower number of tasks that complete the storyline. Before the introduction of the expansion, players had available content from previous versions of the game, denoted by patch 0. Patch 1 was launched on November 13, 2008, and offered the initial content of the expansion with 156 tasks to be performed by players. After about six months, new content was launched with 143 more tasks. The overall content was completed with two additional updates launched 295 days and 421 days after the initial introduction, with 23 and 50 tasks, respectively.[12]

To reduce computational burden, tasks are grouped based on their difficulty levels. In each update, basic content includes individual tasks, which are easier to perform and coded as level 1. Tasks coded as levels 2, 3, and 4, demand progressively more knowledge and cooperation among multiple individuals. The task levels are indexed based on a coding system implemented by the firm throughout all the updates, i.e. levels 1 through 4 belong to patch 0, levels 5 through 8 are in patch 1, and so on. With the introduction of each patch, the set of available choice alternatives

[12] Given that the objective of the paper is to measure the impact of innovation on product usage, the data includes only content related to the game main storyline. There are other unrelated tasks that we do not include in our analysis.

Patch #	Release time (in days)	Age at $t = 1$ (in days)	Size (in MB)	# Tasks in each patch	Task level, coded overall	Available choice set
0	before $t = 1$	363	-	68	1-4	0, 1-4
1	before $t = 1$	163	15,000	156	5-8	0, 1-8
2	$t = 19$	-	740	143	9-12	0, 1-12
3	$t = 131$	-	404	23	13-16	0, 1-16
4	$t = 257$	-	685	50	17-20	0, 1-20

Table 1: Patches and respective tasks.

expands, from an initial size of $J = 8$ to a final size of $J = 20$. The alternatives in the choice set are shown in the last column of Table 1, where $j = 0$ represents the outside good.

In the four years before the start of the analysis period, the firm followed a stable schedule for adding new content to the game, similar to the schedule observed in our data. Although there was not a pre-defined schedule, the time interval between updates varied by only a few weeks. Previous content was also similar in terms of user interaction and most additional content is introduced in a test server available to users, giving an almost perfect knowledge about the quality of content before it goes live and allowing consumers to build expectations about the quality and timing of future updates.[13]

3.3 Player Participation and Progression

The product usage data include actions of 206 users from one of the game servers, for whom the community membership information was also available. These users were randomly selected from all experienced players who were able to access the content introduced on November 13^{th}, 2008. Our data set does not include new players for two reasons. First, the website used as a source of the data provides information about experienced users only. Second, the content introduced by the firm during our analysis was almost entirely dedicated to increasing participation of experienced players. The results of our application should be seen as an analysis of the behavior of these consumers and not of the overall population of players.

For each individual, we observe the date when an action classified by the firm as an achievement was successfully performed for the first time. On average, over the observed time periods, the users

[13] We obtained information about launch dates of expansions and patches from 2004 to 2008, which included more than 30 product updates. We use these data to create an empirical distribution used to define consumer expectations about the schedule of product updates.

in our sample completed 44 tasks out of a total of 440 tasks, with a standard deviation of 32. Figure 1 shows the daily participation of users measured by number of tasks completed, overall and with content divided by product updates. The aggregate usage patterns resemble the typical shape of a product lifecycle, with introduction, growth, maturity, and decline stages. After the launch of each patch, there is an increase in consumer participation, but after several weeks, the interest in the new patch diminishes significantly.

Figure 2 shows the distribution of players across experience levels at the beginning and end of the analysis period and on update release days. As previously mentioned, the expertise level at time t is defined as the highest level of content enjoyed by a user before that day.[14] The numbers indicate the percentage of users at that level, while darker (lighter) lines between levels indicate that more (less) players transitioned between the linked levels. We observe significant gains in player expertise over time, with more than 70% of gamers having expertise of level 4 or below at $t = 1$ and almost 50% of players reaching the highest expertise level of 20 by the end of the observation period.

We conclude this section about product usage by pointing out that even though we only observe the first time a user performs a specific task in the game, each level $l \in \{1, 2, ..., 20\}$ contains a large number of tasks. Hence, it is possible and actually common to see users perform actions of the same level over time, and we observe repeated participation within a level if individuals do at least one other task that has not been done before from the same level.[15]

3.4 Social Interaction

We observe individual membership in game communities for the entire duration of the analysis. In the game, these communities are formal long-term groups of users who agree to cooperate and achieve collective objectives, such as being able to complete more demanding content.[16] Each of these groups - also known as "guilds" - are initially formed by a small group of players and can grow

[14] We note that our data is more detailed than the patterns presented in the figure, since it includes the transition of players at the daily level and not just when product updates are introduced. On the rare occasions when we observed a user do multiple tasks within the same day, we chose the higher level task to code participation on that day.

[15] In practice, if this is a serious concern in other applications, the following change in choice probabilities can be implemented to account for this limitation: every time a consumer completes one achievement included in alternative j, subtract $\frac{1}{C_j} Pr(j)$ from the probability of choosing action j and add it to the outside good probability, where term C_j is the number of tasks included in choice set j.

[16] We note that more challenging content that demands cooperation of multiple players can still be performed by individuals who are not part of a game community. The difference is that to perform these tasks, users form temporary groups just before attempting a task using an option called "looking for group".

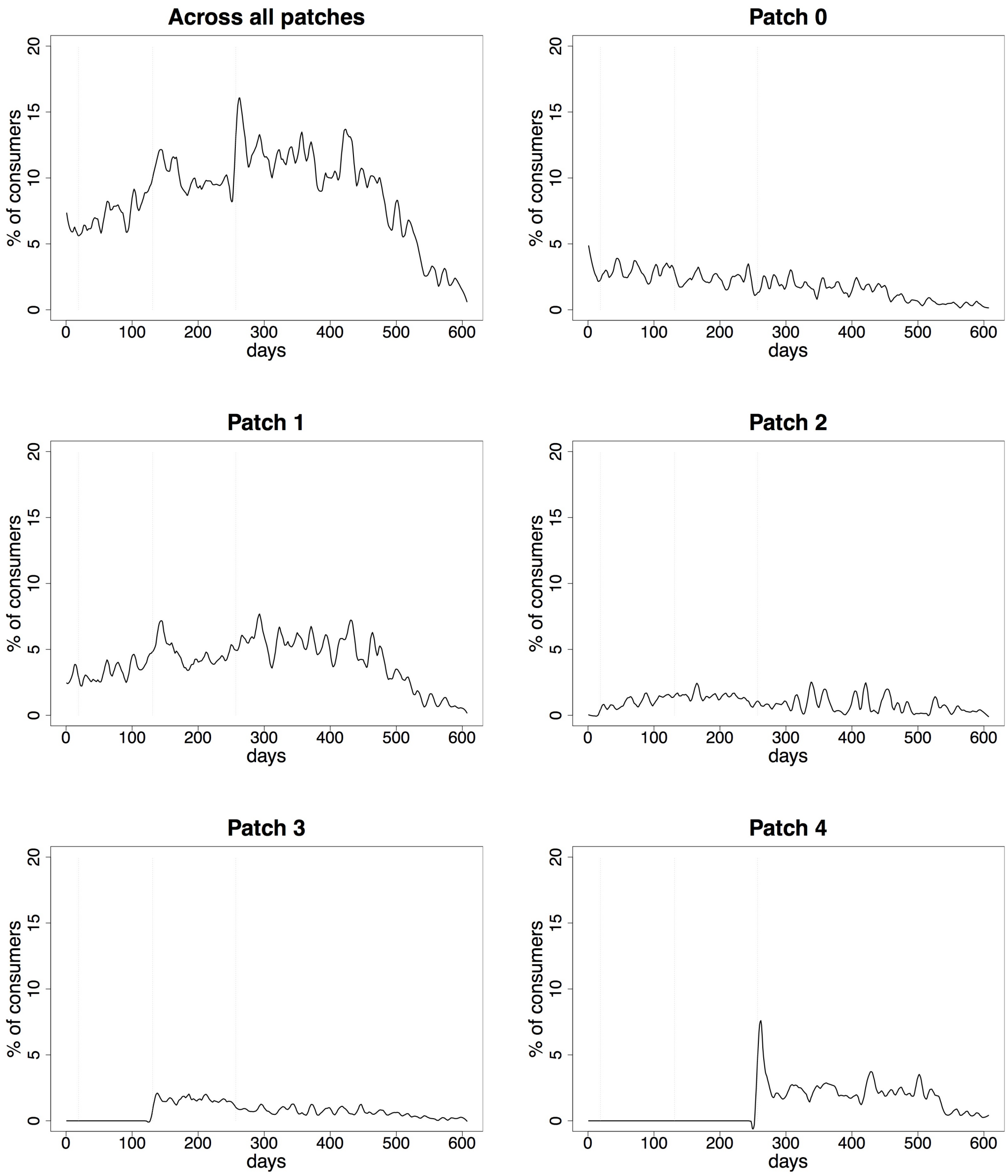

Figure 1: Daily share of gamers who consume game content, overall and by patch.

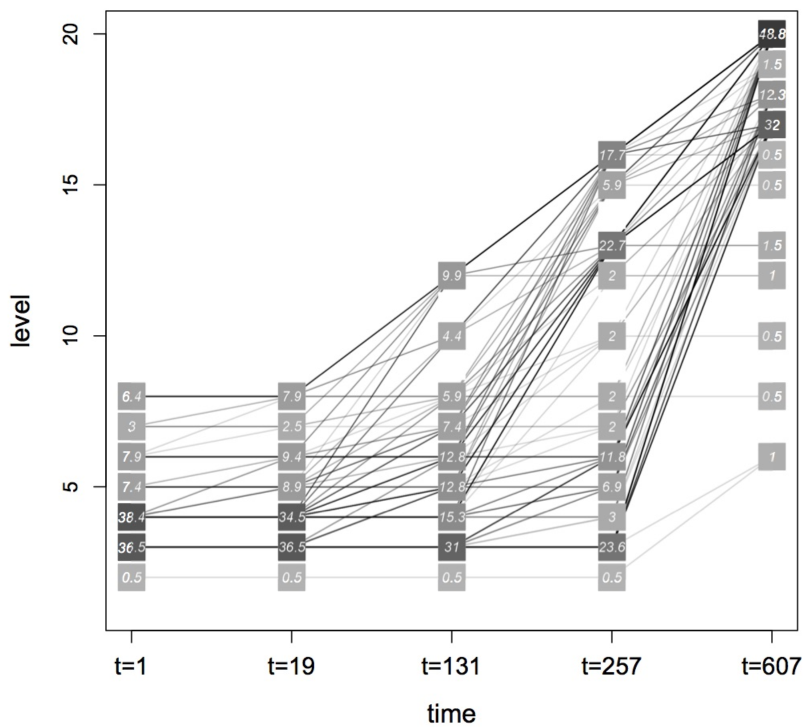

Figure 2: Distribution of experience levels of the players (in percentage) and their progression, presented at the beginning and end of the observation period and update release dates.

to have hundreds of members. Based on information from user forums, the groups have one of two objectives: either be one of the top groups in the game and attempt challenging content or be a casual guild with socialization as the main objective.

The data set contains the dates when an individual decides to join or leave a game community, but unfortunately we do not have additional characteristics about group composition. 91% of consumers in our sample become members of some game community at least once over the period of analysis. At the beginning of our study, the percentage of users in groups was low, about 6%, reaching 28% at the time of the fourth and last product update. Consumers joined an average of 1.5 groups over the time of analysis, as consumers can opt to leave a group and join another one at any point, with minimal consequences to their progress in the game, except perhaps reputation loss with the previous group of players.

Consumers tend to join communities when they get fairly experienced with the product, since the average level of first-time group membership is about 14. We observe that less than 10% of consumers with expertise level five or below belong to a community, while the share of members among consumers with the top two levels is more than 70%. One reason why less experienced consumers tend not to be community members is that they are not viewed as particularly valuable members of the team due to their limited expertise in the game, and we model this aspect in our approach. There is no evidence that consumers change from social to top guilds with time - a consumer that opts initially for a casual guild usually remains in one of that type during the entire analysis period.[17] We observe community members complete tasks with higher difficulty levels than the non-members, as those tasks are more aligned with their advanced game experience, as well as due to the cooperation with other members of their community.

3.5 Consumer Heterogeneity

With the setup described in the model section, the individual-specific components include the in-game group membership state, previous period usage decision, and the experience level with the product. To control for user differences in the empirical application, we introduce both observed

[17]After reading multiple user forums discussions, the decision of changing a group seems not to be primarily driven by prestige. Instead, it appears that switches are due to better matches between the user and the group characteristics (e.g., time of day available for playing) or because of a personal connection to the group. Unfortunately, we do not have information about group characteristics or objectives and hence we do not model this social aspect of match between group and individual members.

and unobserved consumer heterogeneity.

Consumers are endowed with an inherent ability to use the product, constant over time, which is assumed to be observed by researchers based on usage patterns with the product before the analysis period. In our application, the firm published ability measures for each user before the product launch, called badges (a term also used in gamification): how many times an individual successfully completed previous content above a certain complexity. The distribution includes individuals with zero badges all the way up to 2500 badges, with a clear break in the data, with a group of users significantly below 500 badges and another group clearly above that number. Using this information, we divide consumers into two discrete ability groups - high and low-skill players. The parameters of the community membership decision and of preferences for content are made specific to each group.

We also allow for unobserved tastes with a finite mixture of segments g ($g = 1, ..., G$). After testing different number of unobserved segments, we estimate our model with two unobserved segments ($G = 2$), based on fit, number of parameters, and computational demands. Therefore, with two levels of observed innate ability and two unobserved consumer segments, we have four segments in total.

We note again that there is additional heterogeneity - due to individual state dependence - that evolves endogenously because of the change in consumer expertise levels, past usage decisions, the choice of belonging to a community, and competitive effects. We estimate most of the parameters specific to each segment and community membership state because, for example, consumers with higher ability may derive more utility from challenging content and the effect of the match between l_j and l_{it} can be influenced by group membership, because it might be easier for a group of users to provide insights about advanced content.

Finally, skill and group membership have an impact on the success rates of attempting content, w_{ijt} (see Equation 9). In the particular case of our application, users may fail to complete tasks and remain at the same level of expertise. We use data from the website World of Logs[18] about the success rates for different content. This website provides aggregate statistics about the number of times that users attempted and successfully completed tasks in the game. For individual and small group tasks, included in the lower two levels of each product update - levels 5-6, 9-10 and so on - the probability of success is always 100%, as these are easy tasks. The success rates are lower than

[18] accessible at www.worldoflogs.com

100% for the third and fourth level within in each update - levels 7-8, 11-12, and so on. Less skilled no-group individuals have a success rate of around 60% for the tasks of the third level, and 50% for the fourth-level tasks. If users are part of a community, which allows for additional in-game coordination, these rates increase by about 10% while skilled players have an additional 10% chance of completing the challenges, when compared to low-skill players. Hence, the highest probability of completing the more challenging content in each update is about 70% (50% + 10% + 10%) for skilled players that are part of a game community. If user expertise is above or below the content level by at least four levels, these success rates are increased to 100% or decreased to 0% respectively. When a product update is released, the probability of completing any content from older patches is increased to 100%, to reflect the availability to players of more advanced abilities that make old content easy.

4 Estimation

4.1 Identification

Before we describe the estimation algorithm, we discuss the data patterns that identify the parameters in our model. Starting with the content utility function, its intercept is identified by the average observed rates of participation for each content alternative. The parameters of the match value between task complexity and user experience are identified from the observed choices of content levels, given the experience levels of consumers at each period t. For example, a consumer of expertise level 10 can choose to consume any available content, but if she chooses content of level 9, 10, or 11 more frequently, this consumer demonstrates a preference for close-by difficulty levels; if, while at level 10, she does tasks of levels 3 or 4, or a task of level 15 or 16, then content match would not be seen as a benefit. The coefficient will reflect this preference for close or distant tasks in terms of expertise-difficulty match.

The content aging coefficients are identified by the observed time trends in consumption decisions across all content choices of the patch as each product update becomes older. These are separately identified from the content match parameters. While the content aging parameter is the same across all content choices of the patch and is identified through the variation in content consumption as the age state variable evolves, the content match coefficient relates observed content choices to consumer experience levels, which is individual-specific and driven endogenously by consumer actions.[19]

The impact of state-dependence is identified by the observed frequency of successful content completion in consecutive days over all consumers, while the competitive effect is identified by observed differences in actions of consumers above or below the mean level of the user population. Moreover, since the average level of all users is drifting over time, the identity of consumers above and below the mean also changes over time. Hence, variation across both time and individuals identifies the competitive parameter.

For the community membership parameters, the individual data on decisions of joining, remaining, or leaving a group identify the overall costs of joining and benefits from being part of a community, while how the patterns of group membership vary with player expertise identify the relative experience parameter in the utility function of social interactions. We note that a player can stay with a group and not play the game, and we assume that the benefits of being in a group happen even when then consumer is not using the product. This allows us to separate the intercepts from being in a group and using the product, through the observed frequency in the data of remaining in groups versus the frequency of using the product while in groups.

Finally, we discuss the nature of forward-looking behavior captured by the continuation value in the utility function that explains both the decisions of usage and social interactions. For product usage, the dynamic consumer considerations are induced by the extension of choice sets with future product updates and the evolution of expertise with usage to match content to be played in the future. With the expectation that more tasks will be available with the release of product updates and that those tasks are of higher levels than current tasks, consumers have additional incentives to gain expertise with the game. Performing higher level tasks provides consumers with expertise that increases the benefits of more demanding choices and increase completion success rates, although these tasks may be more costly in the present. In the data, we observe consumers attempting higher level tasks more frequently when a product update is about to be released, as they get knowledge and expertise for forthcoming challenging content. For social interactions, the decision to join a group is influenced by the expectation that users will gain from the group by obtaining access to more content and by increasing the success rate when attempting the most challenging

[19]Although the temporal patterns allow for partial identification of content aging, the (quadratic) functional form assumption contributes to its identification, by giving a specific pattern to aging that separates its from other components, such as forward looking behavior.

tasks. Our data show that users play more and at higher levels just before and once they are part of a community, providing support to the forward-looking assumption that users anticipate those benefits when making the decision to join the group.

4.2 Estimation Algorithm

The structure of the consumer choice process within one time period involves making two consecutive decisions: the community membership decision and the choice of content to consume. As such, the two decisions can be viewed as an embedded two-period finite horizon dynamic program with a non-zero termination payoff.[20] Mojir et al. (2013) use a similar formulation.

In the case of the content consumption decision, the researcher observes a consumer's choice of content only if consumer succeeds at the attempted content. To account for this, we use the probability of observing choices

$$Pr'(a_{it}^d|S_{it}^d) = \begin{cases} Pr(a_{it}^d|S_{it}^d), & if\ d=1, \\ Pr(a_{it}^d = j|S_{it}^d)w(j|S_{it}^d), & if\ d=2\ and\ j\neq 0, \\ Pr(a_{it}^d = 0|S_{it}^d) + \sum_{j'} Pr'(j'|S_{it}^d)\left(1-w(j'|S_{it}^d)\right), & if\ d=2\ and\ j=0, \end{cases} \tag{19}$$

where $Pr(a_{it}^d|S_{it}^d)$ are choice probabilities defined in Equation 18 and $w(j|S_{it}^d)$ is the content success rate that is available as data. We note that for the community membership decision, the probability of observing a certain choice by the researcher is equal to consumer's choice probability.

We employ the iterative Expectation-Maximization (EM) algorithm procedure (Arcidiacono and Jones, 2003; Chung et al., 2013) to accommodate the estimation of unobserved consumer heterogeneity in our model. We combine the EM algorithm with the use of the constrained optimization approach (Su and Judd, 2012; Luo, Pang and Ralph, 1996) to reduce the typical computational burden of a dynamic structural model associated with finding the solution to consumer dynamic programming problem. Here, instead of using the nested fixed point algorithm (NFXP) on the Bellman equation to solve for the value function, we maximize the log-likelihood of the model subject to the constraint defined by the Bellman equation. Su and Judd (2012) show that the NFXP and

[20] From the technical point of view, our formulation can be seen as a regular infinite horizon formulation, with the evolution of the membership state from period t to period $t+1$ being stochastic.

the constrained optimization formulations are mathematically equivalent.

We denote the parameters of consumer utility function to be estimated as $\Theta = \{\Theta_g\}$ and the sizes of consumer segments to be estimated as $\Omega = \{\Omega_g\}$, with consumer segment $g = 1, ..., G$. Given observed choices made by N individuals over T time periods, the log-likelihood of observing the data Y is

$$LL(Y|\Theta,\Omega,\bar{V}) = \sum_{i=1}^{N}\left(\sum_{g=1}^{G}\left[Pr\left(i\in g|\boldsymbol{a}_i;\Omega,\Theta,\bar{V}\right)\sum_{t=1}^{T}\sum_{d=1}^{2}log\left(Pr'\left(a_{it}^d|S_{it}^d, i\in g;\Theta_g,\bar{V}_g\right)\right)\right]\right), \tag{20}$$

where $Pr(i \in g|a_i;\Omega,\Theta,\bar{V})$ is the conditional probability that individual i belongs to segment g given her complete history of observed choices a_i, $Pr'\left(a_{it}^d|S_{it}, i\in g;\Theta_g,\bar{V}\right)$ is the probability of observing individual i choose action a_{it}^d, conditional on observed state S_{it}^d and belonging to segment g, and $\bar{V}_g$ is a segment-specific integrated value function.

We will use the integrated version of the Bellman equations shown in Equations 16 and 17 as constraints in the optimization problem. The integrated Bellman equations are obtained using the properties of the extreme value distribution and other standard regulatory assumptions and are presented below in Equations 21 and 22. The optimization problem is given by

$$\max LL\left(Y|\Theta,\Omega,\bar{V}\right) \quad subject\,to$$

$$\bar{V}_g(S^{d=1}) = log\left(\sum_{a\in A_S^{d=1}} exp\left[\overline{u}_g\left(a,S^{d=1};\Theta_g\right)+\sum_{S^{d=2}}\bar{V}_g(S^{d=2})\pi(S^{d=2}|S^{d=1},a)\right]\right) \tag{21}$$

$$\bar{V}_g(S^{d=2}) = log\left(\sum_{a\in A_S^{d=2}} exp\left[\overline{u}_g\left(a,S^{d=2};\Theta_g\right)+\rho\sum_{S^{d=1}}\bar{V}_g(S^{d=1})\pi(S^{d=1}|S^{d=2},a)\right]\right), \tag{22}$$

where $g = 1, ..., G$, and $\overline{u}_g\left(a,S^d;\Theta_g\right)$ is a non-random part of consumer per-period utility function. To avoid the curse of dimensionality, we solve for the value function on selected points in the domain of state variable $\tau_{\tilde{p}}$ that records a number of days that have passed since the release of the most recent product update.[21]

[21] We solve for the value function at the points that are multiples of 42 days and use linear approximation of the value function in the objective function.

The estimation algorithm proceeds as follows:

Step 1. Make an initial guess for the probability that each individual i belongs to segment g, $Pr^0(i \in g|\boldsymbol{a}_i; \Omega, \Theta, \bar{V})$, and assign the starting values to the parameters of the utility function, Θ^0.

Step 2. For each iteration r, fix $Pr(i \in g|\boldsymbol{a}_i; \Omega^r, \Theta^r, \bar{V}^r)$ and optimize the log-likelihood function in Equation 20, subject to constraints described by Equations 21 and 22 to obtain a new parameter set Θ^{r+1} and a new solution to value function $\bar{V}^{r+1}$.

Step 3. Given the obtained parameters Θ^{r+1} and $\bar{V}^{r+1}$, update the probability that individual i belongs to segment g using

$$Pr(i \in g|\boldsymbol{a}_i; \Omega^r, \Theta^{r+1}, \bar{V}^{r+1}) = \frac{\Omega_g^r exp\left(\sum_{t=1}^{T}\sum_{d=1}^{2} log\left(Pr'(a_{it}^d|S_{it}^d, i \in g; \Theta_g^{r+1}, \bar{V}_g^{r+1})\right)\right)}{\sum_{h=1}^{G}\Omega_h^r exp\left(\sum_{t=1}^{T}\sum_{d=1}^{2} log\left(Pr'(a_{it}^d|S_{it}^d, i \in h; \Theta_h^{r+1}, \bar{V}_h^{r+1})\right)\right)}. \quad (23)$$

Step 4. Compute the size of each segment using:

$$\Omega_g^{r+1} = \frac{\sum_{i=1}^{N} Pr(i \in g|\boldsymbol{a}_i; \Omega^r, \Theta^{r+1}, \bar{V}^{r+1})}{N}. \quad (24)$$

Step 5: Repeat Steps 2 through 4, until $\left|LL\left(Y|\Theta^r, \Omega^r, \bar{V}^r\right) - LL(Y|\Theta^{r+1}, \Omega^{r+1}, \bar{V}^{r+1})\right| < \kappa$, where κ is a small constant.

5 Results

We highlight three areas of results. First, we describe fit statistics that show evidence that the model explains the data well. Second, we analyze parameter estimates and discuss the implied importance of diverse motivations of product use. Finally, we present counterfactual scenarios that measure changes in user participation with different innovation patterns and social interactions and discuss managerial implications.

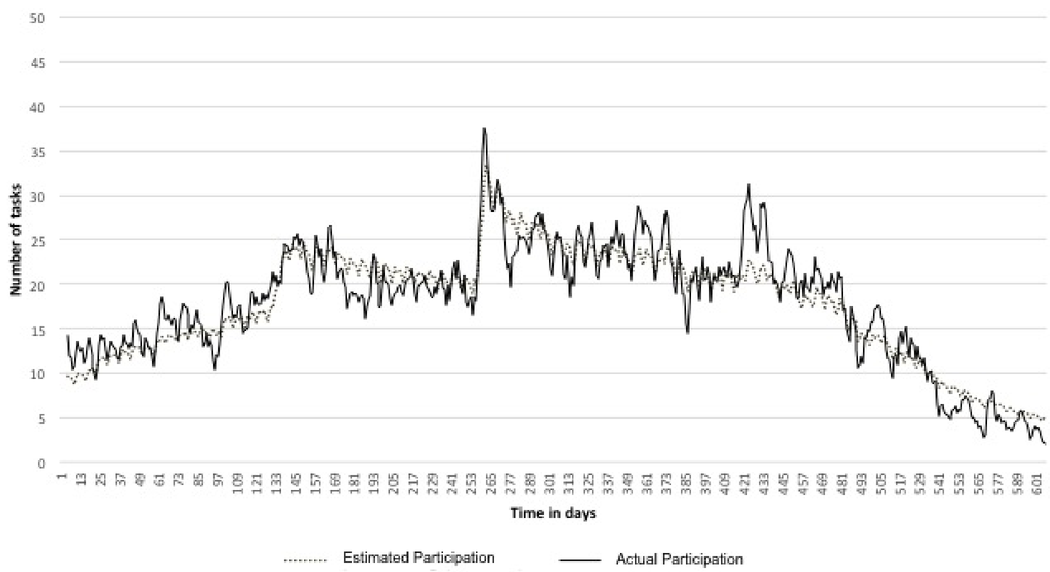

Figure 3: Actual (solid line) and estimated (dashed line) number of tasks performed per day

5.1 Fit Statistics

Having obtained the parameter estimates of the consumer utility function, we predict content consumption using our model and compare the predicted choices to the actual ones. To compute the predicted participation, we aggregate individual choice probabilities across tasks and consumers given the parameter values and data for each time period. Figure 3 shows actual and estimated participation over all tasks of the game. The lines are smoothed for clarity in 5-day intervals. We see that our model explains well the overall patterns of player participation over time. A similar pattern is observed if we disaggregate content consumption by product update in our data.

For our model, the hit-rate across all consumer choices and time periods is close to 90%, while the hit-rate conditional on consumer observable participation (i.e., prediction of the observed task given that a consumer did not choose an outside option) is about 30%, which is a significant improvement over a random guess of 5% given a choice set of 20 content alternatives. The likelihood of our model is significantly better compared to an alternative specification where consumers are myopic.

5.2 Model Estimates

5.2.1 Social Interaction

The social aspect of the product leads to costs and benefits of joining and being a member of a community. Table 2 shows the estimated parameter values for the related components of the utility function.[22]

The decision to join a group is explained by an intercept, with similar negative values of -12.2 and -12.3 for the two consumer segments differing in the observed ability level. The intercept measures the costs of joining a community that are unrelated to the level of expertise. The estimate indicates that, by itself, having more ability does not motivate group membership. However, we find an interaction effect of skill and expertise: the decision to join a group has less costs for higher expertise users, as shown by the positive coefficients when users are above the user population level, but especially so for high-skill users (coefficient of 1.9 vs. 1.6). There are two reasons that explain this result: first, more experienced users are likely to know where to find information and how to navigate the process of joining a community, reducing the cost of joining a group; second, consumers who are both skilled and knowledgeable are sought after by groups because they have demonstrated two important traits: a commitment to the game and skills that can be shared with others.

Our model also takes into account the benefits that come from social interaction, even when a consumer does not play the game. The estimates show that, while remaining a member, a consumer gets significant benefits, especially the low skilled users (0.16 vs. 0.13). In addition, when users gain more expertise, the benefit of being part of a community becomes less important for low skilled users (-0.014) but increases for high skilled users (0.018). This finding suggests that low skilled users benefit from groups when they are starting to interact with content, but as their experience increases, they see less value in the social interactions, while high skilled users benefit more and more from group engagement, explained possibly by a higher status in the group or the enjoyment from teaching others. In addition, it is likely that the later group - skilled and with experience - attempts the most challenging content that is suitable for group play, which provides additional benefits from social interaction and an increased success rate of completing content.

[22]We found the unobserved heterogeneity to be insignificant for the social interaction decisions and present the simpler results with observed heterogeneity across the ability dimension only. We allow for both unobserved and observed heterogeneity for the content choice stage.

Parameter			Low-Skill Users	High-Skill Users
Joining Cost	Intercept	κ_1	-12.216 (0.106)	-12.337 (0.162)
	Dummy above community level	κ_2	1.558 (0.143)	1.908 (0.197)
Remaining Cost/Benefit	Intercept	λ_1	0.157 (0.004)	0.132 (0.006)
	Dummy above community level	λ_2	-0.014 (0.005)	0.018 (0.006)

Table 2: Social interactions: parameter estimates, with standard errors in parenthesis

5.2.2 Content Consumption

Table 3 presents the estimates with standard errors shown in parenthesis for the content choice decision, for the four discrete segments. [23] The estimates of base interceptsα_i indicate significant consumer heterogeneity in the propensity to consume content, but little heterogeneity between members and non-members of a product community. Segment 3, composed of skilled users and with an estimated size of 16% of the overall population, gets the highest satisfaction from content with the least negative intercept (-5.1), while segment 2, with 19% of players, has the most negative intercept (-10.4). Segments 1 and 4, with the remaining 16% and 32% of the market, show a playing propensity that lies between the propensities of the aforementioned segments. The four intercepts for community members are not statistically different from the respective parameters for consumers who do not belong to a game community.

The estimates describing the match between consumer experience and content complexity levels reveal that consumers prefer content that fits well with their expertise, as coefficients for all segments are negative: as the distance between content and user levels increases, enjoyment of content decreases significantly. This is especially true for tasks with complexity above the consumer's experience level, which appeal much less to consumers. In general terms, this is similar to the disutility of a consumer trying to use advanced features of a product before understanding basic features or watching a new episode in a television series after skipping the previous one. The different consumer segments show disparate reaction to this mismatch. The strongest impact is on segment 3, who has the highest preference for tasks closer to their level. This result implies that these consumers prefer

[23] For clarity of exposition, we do not present the $J-1$ intercepts of each choice ($J-1=19$) nor the X_t coefficients for each weekday in Table 3. For the alternative intercepts, they vary between 0.16 and 1.27, with the second product update having the most positive intercepts. Before our analysis period, and looking at past records of the game, we found that content at the middle of each expansion is usually the most valuable to users, by providing a strong progress or completion of the storyline behind the game, which justifies the knowledge of quality of content by consumers before launch. For the weekday intercepts, they vary between -0.13 and 0.33. The higher estimates are for Saturday and Sunday, when users have more time to play the game.

Parameter			Low-Skill Users Segment 1	Segment 2	High-Skill Users Segment 3	Segment 4
Base Intercepts	Non-Members	α_{00}	-5.482 (0.488)	-10.0585 (0.341)	-5.1381 (0.309)	-7.077 (0.331)
	Members	α_{01}	-5.827 (0.481)	-10.3698 (0.346)	-5.1179 (0.330)	-7.153 (0.365)
Content Match - Lower	Non-Members	γ_{10}	-0.048 (0.010)	-0.049 (0.009)	-0.074 (0.006)	-0.008 (0.004)
	Members	γ_{11}	-0.017 (0.012)	-0.025 (0.008)	-0.090 (0.006)	-0.013 (0.008)
Content Match - Higher	Non-Members	γ_{20}	-0.349 (0.045)	-0.421 (0.039)	-0.913 (0.032)	-0.686 (0.023)
	Members	γ_{21}	-0.169 (0.0714)	-0.059 (0.029)	-0.767 (0.042)	-0.440 (0.052)
Competitive Effect		δ	0.036 (0.068)	0.077 (0.057)	0.118 (0.069)	-0.196 (0.044)
State Dependence		μ_1	1.845 (0.056)	1.814 (0.053)	1.115 (0.024)	1.606 (0.048)
Aging of Content	Product Update 0	β_{01}	0.709 (0.173)	1.590 (0.087)	0.460 (0.122)	0.578 (0.088)
		β_{02}	-1.024 (0.156)	-1.107 (0.056)	-0.533 (0.099)	-0.416 (0.057)
	Product Update 1	β_{11}	1.972 (0.162)	2.604 (0.080)	1.134 (0.044)	1.244 (0.028)
		β_{12}	-2.058 (0.154)	-1.796 (0.067)	-1.325 (0.054)	-1.019 (0.027)
	Product update 2	β_{21}	0.621 (0.440)	2.554 (0.243)	-0.355 (0.065)	0.120 (0.084)
		β_{22}	-1.226 (0.750)	-3.048 (0.313)	-0.223 (0.143)	-0.264 (0.126)
	Product update 3	β_{31}	-0.579 (0.223)	2.092 (0.274)	-1.394 (0.066)	0.348 (0.876)
		β_{32}	-0.469 (0.564)	-3.141 (0.483)	0.997 (0.174)	-1.390 (0.133)
	Product update 4	β_{41}	-2.015 (0.313)	3.792 (0.198)	-1.370 (0.141)	1.141 (0.140)
		β_{42}	2.970 (0.994)	-8.794 (0.464)	1.741 (0.350)	-3.440 (0.344)
Segment size		Ω	15.5% (0.00%)	18.9% (0.00%)	34.0%(0.01%)	31.6% (0.01%)

Table 3: Content consumption: parameter estimates, with standard errors in parenthesis

to follow the natural progression of the game, building experience in smaller increments without skipping content. As mentioned before, this is also the segment that has the highest preference for the game (highest intercept in the content choice utility function). The other three segments show lower sensitivity to the match between their experience level and the level of a task, with coefficients closer to zero.

Looking at the impact of group membership on content match, consumers who are part of a community show a reduced effect of not having enough experience to fulfill more complex tasks, with coefficients of the distance to higher-level tasks taking values significantly lower, in absolute value, to those of consumers who decided not to join a group of other users. This finding is evidence that collaboration across users within groups is prominent, with more experienced users frequently helping novice users to engage with more demanding content.

Finally, the competitive effect is significant for all segments, but especially so for the two skilled segments: segment 3 with a positive coefficient, and segment 4 with a negative effect. The segment 3 seems to be composed of consumers that gain additional satisfaction from the prestige of being ahead of the curve, while segment 4, even if highly skilled, is likely composed of laggard players that are commonly below the average expertise level of other users.

5.2.3 State Dependence and Aging of Content

In terms of in-game state dependence, low skill players increase their usage significantly when they successful complete content in the previous day, similar to habit formation. In contrast, the segments with higher ability show lower state-dependence coefficients and demonstrate less of habit formation traits. This might be explained by the fact that more skilled players are likely to play other games as well and intersperse usage, thus lowering the effect of previous day consumption.

We also evaluate a longer trend impact of content aging, which could be due to other complementary or competitive technologies or services that might increase or lower the appeal of the product, even without consumer usage. Interestingly, the segments look more similar across skill groups than within: for example, coefficients are more similar for segments 2 and 4, which have different skill levels. These two segments have the lowest propensity for playing the game, and potentially, as uncommon users of the product, perceive almost no aging of the product over time. Segments 1 and 3 have higher propensity to use the product but also are more sensitive to aging of the product, with the appeal of content lasting for shorter time periods after the launch of a product update.

In addition, there are noticeable differences in content aging across product updates. While content introduced earlier in the product lifecycle generates consumer interest that endures for most of the analysis period, later content does not have the same resilience. This result can be explained in two ways. First, we believe that this is an outcome of the nature of product updates. Earlier updates brought new elements to the game and were considered pioneering, while later product updates built upon content previously introduced. The pattern where the introduction of updated content or products has a higher impact for earlier and pioneering innovations compared to later and non-pioneering product updates is also present in other product categories, for example in the auto industry (Srinivasan et al., 2009). In television series, the same pattern is also common, with subsequent seasons of a show attracting increasingly fewer audiences. Second, it is possible that there are demand changes that occur over time and lead to either different participation rates or different consumer segments enjoying the product. This argument agrees with a quote from the CEO of Blizzard Entertainment, who mentioned that players have been increasing the speed of content consumption. In the next section we display the usage patterns showing that different segments consume content at different periods, which also explains the variation in the aging speed across product updates.

5.3 Usage Patterns and Motivations

For further analysis of product usage and progression patterns, we assign each gamer to a particular segment based on the highest estimated individual probability of segment membership $Pr(i \in g)$.[24] In the four panels of Figure 4, we show the evolution of the experience levels of each segment measured as the average experience level of all players in that segment and the evolution of the average experience level of the user population in our data set.

We observe that the evolution of experience is significantly different across segments, explained by the aforementioned interpretation of the estimated parameters. Segment 1 consumes and progresses through content promptly after the introduction of the product: given the somewhat high usage propensity of these individuals, they seem to be unskilled but eager players, who prefer to progress in the game immediately after new content is made available. Segment 3 shows a similar pattern but with a main difference that these users progress much faster, in part justified by their higher skill, which allows them to become experts earlier than most. Segments 2 and 4 have lower propensity to play and are also laggards in content consumption, especially the low-skilled Segment 2. Overall, these two segments are slower at progressing through experience levels and only enjoy part of all available content.

Interestingly, the differences between the average experience levels of the four segments is significantly larger in the initial stages of the product lifecycle, but shrinks towards the end, when more serious users do not have new challenging content to improve experience and stop using the product, while the two laggard groups catch up. This is an important finding for two reasons: first, it reveals that more advanced content is important for almost all types of players, and not just for the smaller segment of innovator hard-core players; second, the reduced heterogeneity in experience is likely to allow any player to adopt future product expansions that continue the story at the end of the analysis period, which is beneficial to the continuity of consumer engagement with the product.

To illustrate the relative importance of consumer motivations for content choices, we compute the

[24] The probability of belonging to one of the three segments is above 85% for most individuals.

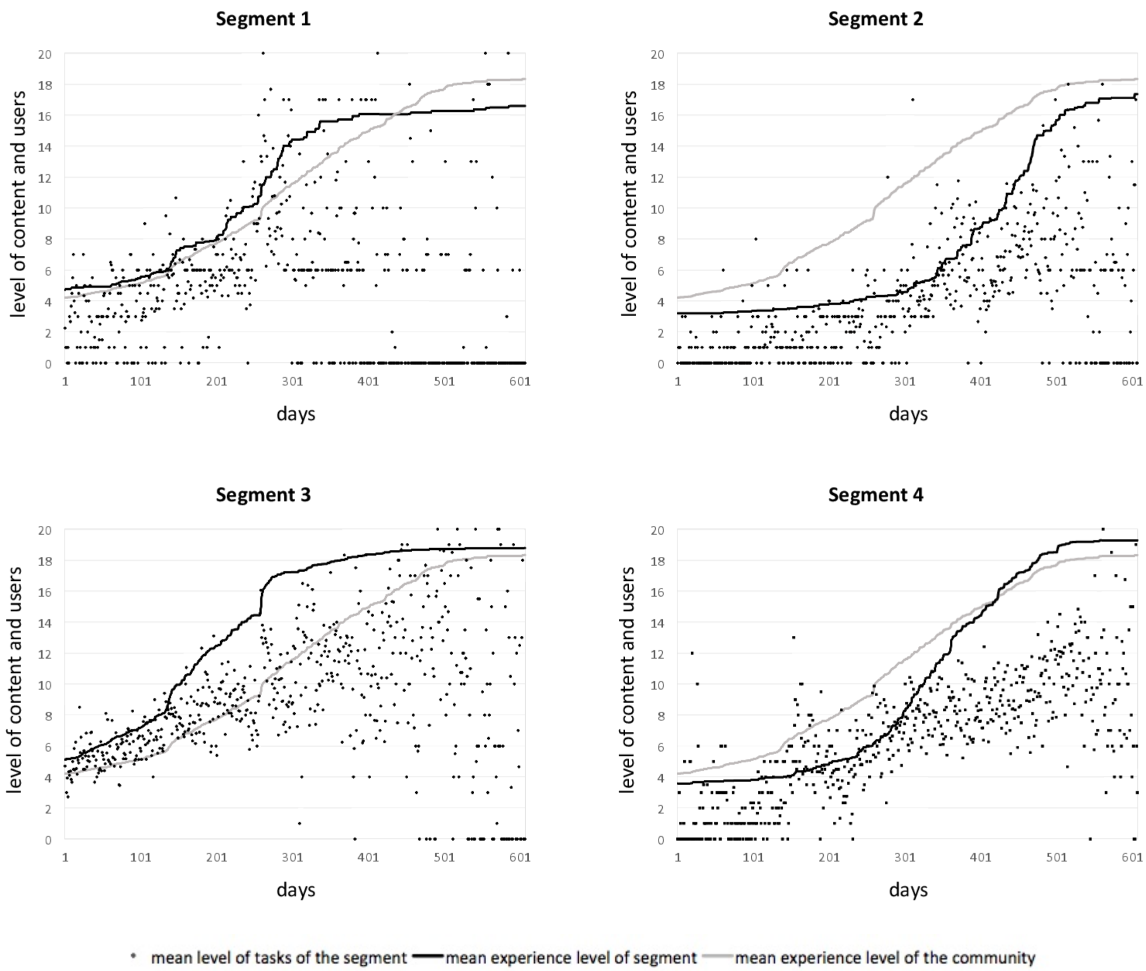

Figure 4: Evolution of the user level, the mean level of the user community, and mean of the content choices.

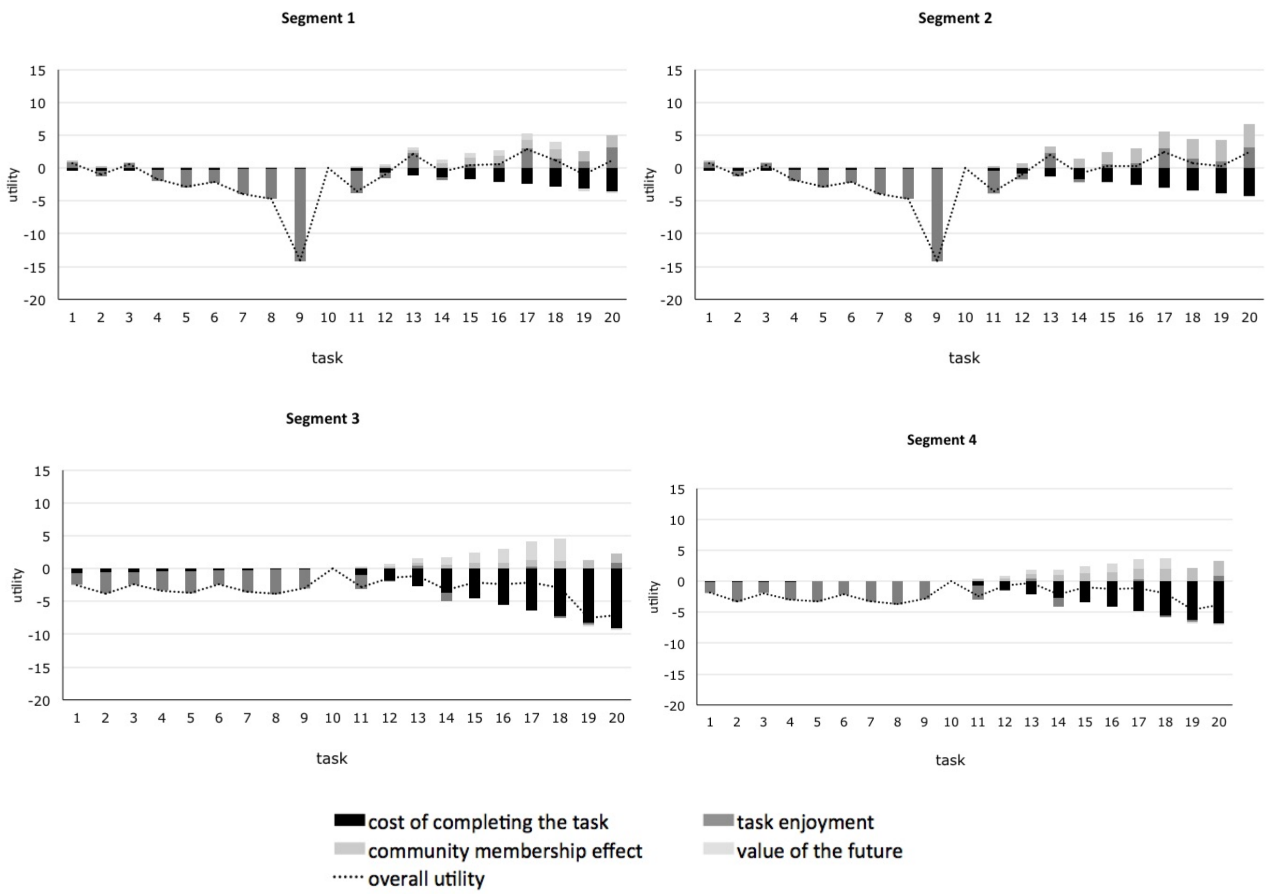

Figure 5: The components of consumer utility that impact the choice of content, shown across game tasks and consumer segments. We normalize the utility of task 10 for segment 1 to zero. The consumer state includes experience level *l=10*, $t = 257$, and consumer is a community member.

utility components for an individual with experience level $l_{it} = 10$, member of a product community, at the time of the introduction of the fourth product update ($t = 257$). The panels in Figure 5 show the results by segment and content choices $j = 1, ..., 20$. We normalize the task utility components against the values from task 10.

Overall, the importance of usage motivations is significantly different across content. The impact of match between user expertise and content complexity, denoted as the cost of completing a task, is felt for tasks of complexity far and above the user's expertise, especially for segments three and four. Although these segments are highly skilled, they prefer not to skip content and match almost perfectly their expertise level to the complexity level of content. This negative impact of the mismatch between experience and complexity of content is compensated by the positive effect of belonging to a community and the future benefit obtained from trying ambitious tasks. For

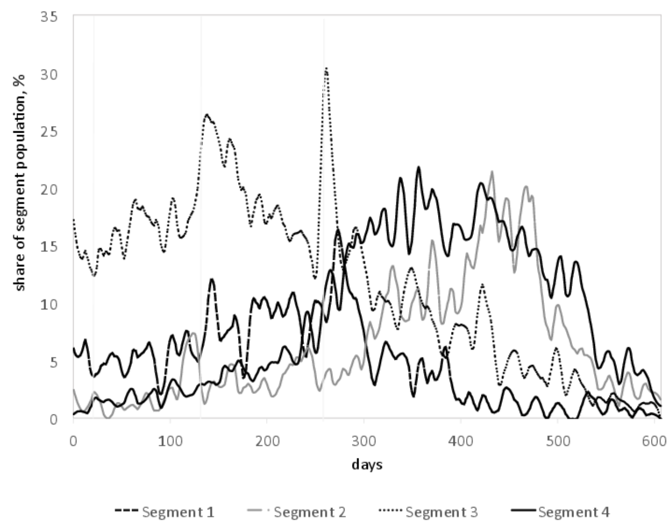

Figure 6: Participation by consumer segment. The vertical lines denote patch introductions at $t = 19$ (patch 2), $t = 131$ (patch 3), and $t = 257$ (patch 4).

segments one and two, the main usage driver is the intrinsic preference for the product. Across all users, product usage of simpler content is primarily motivated by intrinsic preferences, while group interactions and future benefits of gaining experience from using the product are relatively more important to explain consumption of more complex content.

In Figure 6, we aggregate content consumption over all tasks and show temporal differences in observed product usage by segment. The figure shows that segment 3 includes highly-skilled early adopters, with large increases in observable participation immediately after the introduction of new content; segment 1, although also starting usage early, does not have the skills or propensity to use the product as often; and segments 2 and 4, the remaining half of the market, participate more frequently after the second product update and are less influenced by innovation.

Three additional conclusions can be drawn. First, patterns of usage are similar to overall patterns of a product's lifecycle often shown for product purchase or adoption, with an introduction, growth, maturity, and decline stages. Second, our results show that when product updates are frequent and, even though users in our sample are experienced and familiar with the product, there is a clear distinction between innovators and laggards, in terms of timing of usage and of response to innovation. Third, heterogeneity in experience at the end of a product usage lifecycle is considerably less than at early stages of product usage.

Finally, we investigate the decision to be part of a product community for each consumer segment. We observe that the social membership decision follows the usage decisions closely: as users become more experienced and enjoy more demanding content, they join a group of users to collaborate and share the enjoyment of content. Segment 3 is the fastest to form groups, while the other three consumer segments include gamers that prefer individual experiences, and only late in the product lifecycle do they decide to become part of a group. Surprisingly, in the later periods of the product life, more than 70% of users enjoy being part of a product community, reflecting reduced heterogeneity in the consumer population. We discuss further implications of social interactions in the next section.

5.4 Managerial Implications

The usefulness of building a model based on consumer primitives and expectations is illustrated in this section by three simulations that match the managerial problems discussed in the introduction. As previously mentioned, managers are increasingly concerned with how fast content is being consumed or how engagement can be motivated through product design or social interactions. Using our model, we first measure the impact of changing the timing of a product update introduced during the analysis period. Second, we look at content design and test a change in content complexity by simulating a change in the "distance" between the expertise of a user and higher level content requirements. Third, we quantify the effect of providing incentives that reduce the costs of engaging in social interactions between users. Social components in product usage are becoming very important for most categories, as managers attempt to lead users to social media platforms to generate content and connect with other users with similar preferences.

5.4.1 An Alternative Innovation Schedule: When Should Managers Launch New Content?

Our approach can be used to provide insights about alternative scheduling of product updates. In our data, we observe most updates concentrated in the first half of the product lifecycle, leaving almost 300 days without a major product update. In this section, we run a counterfactual scenario where the launch of the fourth update is postponed by about two months, from day 257 to 312, with consumer expectations regarding the update timing remaining the same as in the actual scenario

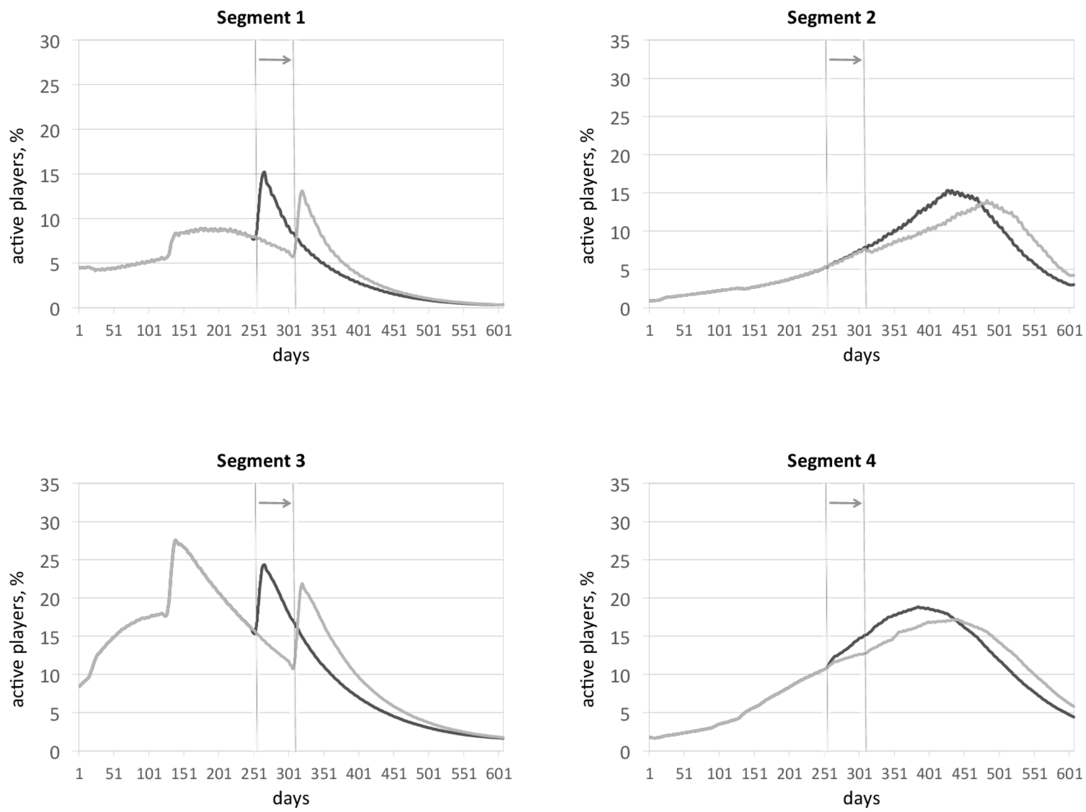

Figure 7: Impact on segment participation of postponing product update 4 from day $t = 257$ to day $t = 312$. The black line shows the actual participation within each segment, while the gray line shows the counterfactual one (smoothed over a 5-day window).

to reflect the idea that the delay was neither planned nor communicated by the firm. This setting reflects a trade-off that managers may face: launch content earlier to motivate a fast increase in participation from a large community of users or pace the introduction of new content to keep engagement higher for a longer period of time.

Figure 7 shows the comparison between the actual and counterfactual participation, measured by the share of active users.[25] The postponing of the last update leads to an initial drop in participation due to the lack of innovative content for the two months. However, the drop in participation is compensated by an increase in participation in later time periods after the delayed content was finally released. Despite the fact that we observe similar participation in the actual and counterfactual scenarios, the timing of consumption is significantly different, especially for segments

[25] In the actual scenario, we use the stochastic belief about the timing of introduction, as in the estimation.

1 and 3 of more highly skilled users.

In net terms, postponing the product update has a negative impact with overall participation going down by about 2% and indicating that the firm was correct at launching more content earlier on in the product lifecycle. By simulating different launch dates, the proposed model can be used to inform managers about optimal innovation schedules. The results also provide evidence that managers can use the timing of innovation to influence usage patterns and avoid excessive peaks in demand that the firm cannot satisfy, for example due to server capacity.

5.4.2 Change in Product Difficulty: Should Managers Make Content More or Less Challenging?

To measure the impact of how challenging content affects consumer participation, we run two counterfactual scenarios where the third product update is modified and its perceived difficulty is either doubled or halved. To implement these scenarios, we increase or decrease the "distance" between a user expertise level l_i and the level of content complexity l_j required by a task of higher level. In other words, the term $|l_i - l_j|$ is multiplied by 0.5 or by 2 for all tasks of product update 3, in the cases when $l_i < l_j$. In practice, the firm can redesign product and increase or decrease the required expertise necessary to complete content at different stages, affecting the match between user and content.[26] This is a relevant set up as, on the one hand, more complexity leads to longer times required to reach higher levels and hence prolong usage. On the other hand, if content is perceived as too difficult, it may dissuade players from attempting it and lead to churn. Since we are simulating both an increase and decrease in difficulty, it is also interesting to detect asymmetric responses to changes in product design.

In Figure 8, we show how consumer participation changes. For segments 1 and 2 of low-skilled users, the impact of increasing or decreasing the perceived difficulty of the game on their behavior is almost null and it is not important in the decision to use the product, as they are motivated mostly by enjoyment of each task without worrying so much about the more challenging content, as their parameters γ_{20} and γ_{21} are significantly closer to zero. For segments 3 and 4 - with higher skill - an increase in perceived difficulty lowers participation, while lowering difficulty provides incentives to

[26] An alternative way to implement an increase in content difficulty would be the change the success rates of completion.

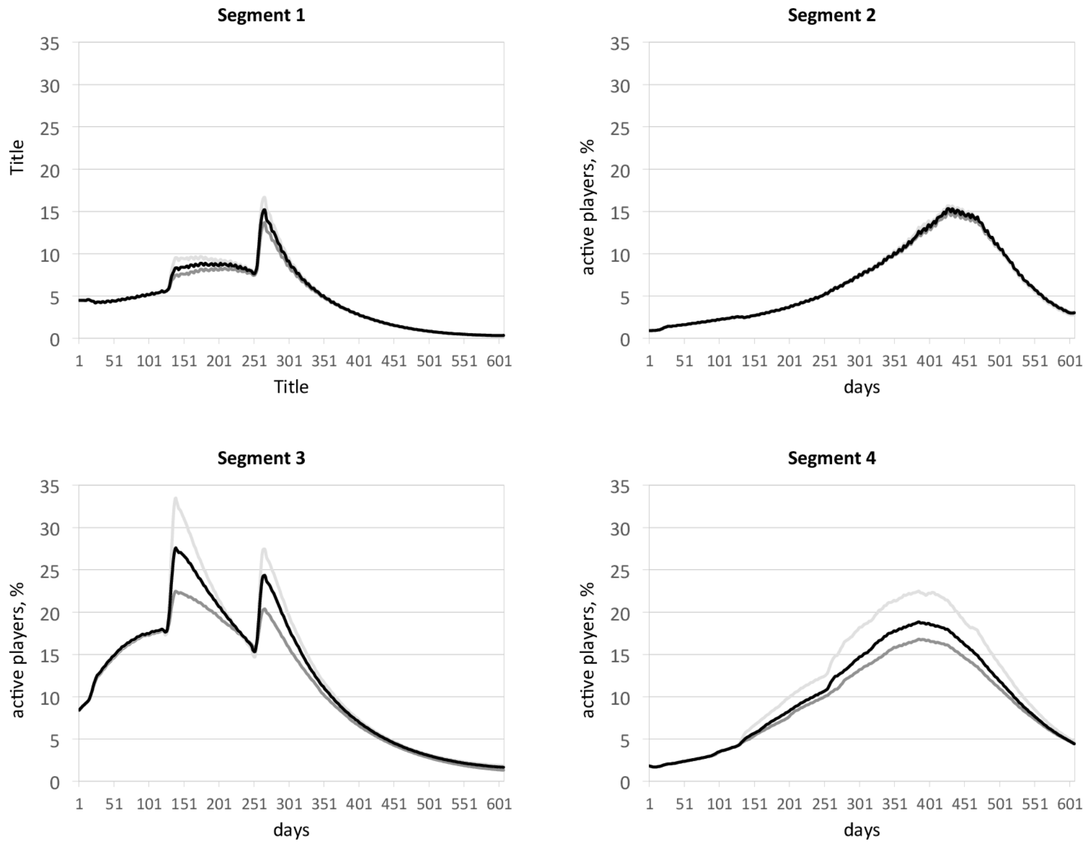

Figure 8: Impact on segment participation of changing content complexity of product update 3 on day $t = 131$. The darker line displays participation in the lower complexity setting, the lighter line reflects higher complexity, while the middle line shows the actual scenario.

participate more.

Lowering the perceived difficulty of higher level content has an overall positive effect. However, this decrease is likely to cause negative impact in later stages of the game. For example, just before the launch of update four in time 257, segment 3 does play more in the high complexity scenario, and it was only the introduction of new content that prevented an increased drop in engagement in the low difficulty setting. Overall, this illustrates a likely trade-off between making the product less complex to increase initial usage and increasing the speed of updates to keep consumers interested.

We conclude that higher content difficulty is negative to usage in our setting, leading players to abandon the game. In fact, it seems that the current set up of the game is too challenging for players that want to progress faster, without any main benefits of keeping engagement higher for longer periods of time. The counterfactual where difficulty is lowered confirms this effect, with a positive impact on short term participation, although the simulated change is close to showing negative effects on later stages of the game because users consume content too fast. Managers can use the proposed methodology to test different combinations of speed of innovation and complexity levels before launching new content in the market.

5.4.3 Lowering Costs of Social Interactions: What is the Benefit of Motivating Social Interactions?

In many product categories, companies facilitate social interactions between users, for example through the creation of online forums, public relations events, or websites in social platforms. In the case of our application, the firm has over the years implemented a number of tools that allowed easier access to groups, such as a in-game "Search for Guild" option and expanded the social dimension with game-related forums, where communities from different regions around the world - for example, West Coast and East Coast in the United States, Europe, and Oceanic areas - can look for additional members and where individual users can advertise their interests for groups.

To measure the effect of an incentive to social interactions within our model, we reduce the fixed portion of the estimated costs of joining a group - measured by parameter κ_1 - by 25%. In practice, any tool that facilitates in-game social interaction for all users impacts k_1. Alternatively, our model can quantify firm actions that specifically affect more experienced users - such as making it easier for expert players to advertise their group in the world environment or facilitate the transmission of knowledge to beginners - through changes in the parameter κ_2.

The results are presented in the two panels of Figure 9. On the top panel, we show the evolution of the average level of users, while the lower panel reveals the percentage of participating users, for both the actual and counterfactual cases. Overall, the decrease of 25% in k_1 increases membership in groups by an average of 40% across all periods, for example, from 10% to 14% by the second update, which has two implications illustrated in Figure 9. First, as the bottom panel shows, consumers are more active with the content. This engagement is especially important in later stages of the game when there is a tendency to abandon the game as content gets older. In fact, in the second half of the life cycle, this effect is most pronounced, getting almost twenty percent increase in participation from period 350 to 450. After that, due to boredom and no new content, social interactions do not impede gamers from moving on to the outside alternative and leaving the social groups and the

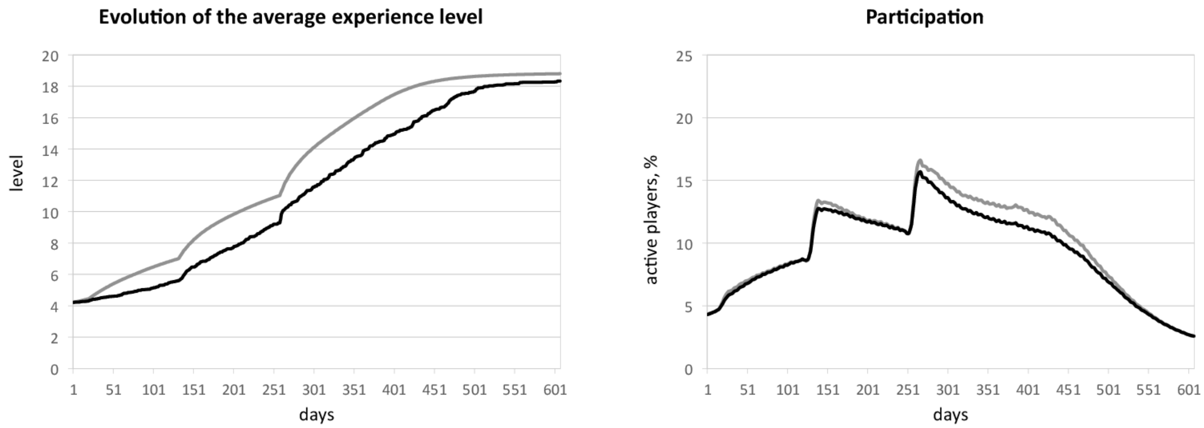

Figure 9: Impact on average level progression and participation of lowering costs of joining a group by 25%. The black line shows the actual setting, while the gray line shows the counterfactual scenario.

game.

Second, consumers reach higher levels and are able to enjoy more content than they would when not part of a group. The average level of content consumed increases by around two levels, a 10% increase in relative terms, indicating that users become more experienced with the game, are able to succeed at tasks that they could not do on their own, and learn from others. Even though content is consumed at higher rates, this does not lead to lower content consumption in later stages because the amount of available tasks is large enough so that the benefits of usage outweigh the fact that consumers may become bored faster. This is somewhat similar to the situation that we observed in the difficulty counterfactual: making content accessible to users, either by lowering its difficulty or increasing social connections, has strong benefits to participation because, in the observe setting, the game has significant amounts of content that users never attempt, complemented with frequent updates. In summary, we find that the impact of social interaction leads to significantly higher and longer engagement with the product and our proposed model is able to quantify this effect.

6 Conclusion

In this paper, we propose a model of content consumption by forward-looking consumers. Our framework is applicable to a number of product categories where experience and involvement with a product are formed by frequent usage, such as video games, TV shows, mobile applications, book series, and, in more general terms, any durable good where practice is essential to develop the expertise necessary to use advanced product features.

Our approach sheds some light on the link between usage and the introduction of new content. Using data from the popular online game "*World of Warcraft*", we find that motivations for product usage vary for different content. For basic content, intrinsic preferences for the product dominate the decisions, while for complex content, social interactions and future benefits resulting from gains in expertise become increasingly important. In terms of innovation, we show that product updates drive significant use of the product, but that this effect is reduced in later introductions, both in terms of initial usage and longevity of consumption. Our results show that four distinct consumer segments respond very differently to innovation. A relatively small but skilled segment of "serious" players consumes content early and at a fast pace. The other three consumer segments, although slower to consume the content, still reach similar level of experience with the product as the "serious" segment, but much later in the product life cycle. Substantively, our model can be used to answer three important managerial questions: (1) When should managers launch new content? (2) Should managers make content more or less challenging? (3) What is the benefit of motivating social interactions?

There are several avenues for future research. For example, our approach is focused on product usage and the purchase decision is not modeled. In cases where there is no purchase (e.g., TV series) or when pricing options such as a time-subscription (online games) offer a direct link between revenues and participation, this limitation is less severe. However, in products where consumers need to pay to obtain additional content or when prices vary, we would need to simultaneously explain purchase and usage, because while deciding to further engage with the product, a consumer anticipates that she will need to pay for more content in the near future. We leave this question to future research.

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