The XaaS Life Cycle: Buzzers, Adopters, Users, Money*

Barak Libai
Arison School of Business, Reichman University (IDC), Herzliya
libai@runi.ac.il

Eitan Muller**
Stern School of Business, New York University, New York
Arison School of Business, Reichman University (IDC), Herzliya
emuller@stern.nyu.edu

Verena Schoenmueller
ESADE Business School, Barcelona
verena.schoenmueller@esade.edu

* The authors would like to thank IJRM Editor, AE and two reviewers for constructive and helpful comments on a previous version of this manuscript. The research was supported by the Israeli Science Foundation.

** Corresponding author

The XaaS Life Cycle: Buzzers, Adopters, Users, Money

Abstract

With the rise of recurring consumption models much of the research on new product growth has become less relevant to modern markets. Historically, this research centered on first-purchase models tailored for durable goods, where adoption served as a strong proxy for profits. However, the rise of recurring consumption business models—often termed XaaS, or "everything as a service"—now characterizes many new product sectors. Within the XaaS framework, adoption merely signifies the beginning of the growth of a user base and a continuously evolving revenue stream. Managers, investors, and analysts in the XaaS realm, who focus on the evolution of revenues and profit over time, therefore require an innovative lifecycle view. However, the shift towards XaaS thinking remains underrepresented in how marketing researchers understand the product growth lifecycle.

This article introduces a comprehensive framework for examining XaaS growth. We propose that understanding XaaS growth demands an examination of a three-tiered sequence: Adopters, Users, and Money. We offer insights into the trajectory of these tiers and their interconnections and outline the ramifications of redirecting new product growth research toward the emerging XaaS landscape.

1. Introduction

The beginning of the *Software as a Service* (SaaS) revolution has been attributed to Marc Benioff, founder and CEO of Salesforce, who in the late 90s while still at Oracle, observed that with the then predominant licensing model of software, firms needed to pay high licensing fees upfront, and rapid technology advancements made the software application obsolete quickly. This resulted in a slow adoption and diffusion of many enterprise software solutions that would have diffused much faster with a subscription-based pricing model (Miller 2018; Bhattacharya and Bhattacharya 2021). Fast forward 25 years, the recurring consumption model, for which the profitability of the product-service business stems from a continuous relationship with the consumer over time, is becoming the predominant business model in numerous markets (Tzuo and Weisert 2018; Chen et al. 2018).

The dominance of recurring consumption among new products is, of course, not limited to software. Service-based thinking has been recognized for a while as governing the dominant logic of marketing in markets that have not traditionally been considered service industries (Vargo and Lusch 2004; Rust and Huang 2014). Digital teachnologies accelerate the process of *servitization* where product firms infuse service into their offering, often moving the offering to pure services (Favoretto et al. 2022; Kowalkowski et al. 2017). Thus, the growing markets for recurring consumption products have been referred to as ***XaaS*** – "everything as a service" (Bertini and Koenigsberg 2020; Bhattacharya and Bhattacharya 2021).

Given the ubiquity of XaaS among new products, it is notable that we have limited insights into the fundamental way XaaS grows. Recognizing the shape and dynamics of growth is essential for predicting, launching, valuing, and managing new products, so these analyses are of key significance for marketers (Chandrasekaran and Tellis 2018). Researchers have therefore explored the expected shape of growth and turning points such as the timing and extent of takeoff, the "saddle" during growth, or the timing and the size of the peak (Mahajan, Muller and Srivastava 1990; Golder and Tellis 2004; Chandrasekaran and Tellis 2018; Goldenberg Libai and Muller 2002; Goldenberg, Libai and Muller 2010). However, these efforts largely considered the first adoption over time and have been primarily applied to durable goods. Even when the growth patterns of service products were analyzed, they were examined mainly via models focused on the first adoption in the market (Peres, Muller and Mahajan 2010).

We argue here that the distinction between XaaS and durable products is substantial and requires a new perspective on "growth". A key difference is the XaaS discrepancy between adoption and monetization. When looking at new products, firms and investors' final focus is the stream of customer profits that is anticipated to arrive. Since durables' monetization happens at adoption, durable adoption growth provides a picture of the number of users and the money created over time, and can be used for prediction and planning. In contrast, for an XaaS product, the adoption is just the start of a relationship. Indeed, the number of users, not adopters, has become the center of attention and reporting for many XaaS firms. Social media entities (such as Facebook and Twitter), streaming entertainment services (such as HBO and Netflix), and direct-to-consumer firms (such as Blue Apron and Dollar Shave Club) are examined and evaluated on the pattern of user growth.

This raises several issues. First, given the past interest in the shape and turning points of the adoption curve, it is interesting to note that we know little about the shape of the user curve. Second, whether the user curve provides the full information about monetization is unclear, as there may be a temporal difference between the spending on acquisition and the eventual cash flow customers create over time. Finally, we need to understand better how customer-related variables affect the relation of the lifecycle turns and a XaaS product's profitability. Customer churn, for example, can affect the number of users directly via the change in the number of adopters who stay and indirectly through social influence on potential new adopters. This suggests that we need a broader view of the life cycle of XaaS products that goes beyond the adoption curve.

Past research, however, can only provide limited insights into this issue. In the last two decades, researchers have begun to combine adoption and customer relationships to model the growth of service-like products (Gupta, Lehmann, and Stuart 2004; Libai, Muller, and Peres 2009; Schulze, Skiera and Wiesel 2012, McCarthy, Fader and Hardie 2017; see Table 1). Yet, the focus of this research stream has been on customer equity measurement and its relationship to valuation, as well as on optimal resource allocation, but not on XaaS growth patterns. While XaaS growth may have been modeled as part of the measurement process, the growth pattern, what can affect it, and the relationship to profitability, are yet to be explored.

Our aim here is to provide a step in this direction, proposing an underlying framework and providing initial insights. Our fundamental claim is that understanding XaaS products' growth requires the consideration of three growth patterns that jointly create the XaaS life cycle picture. The first is, like in the case of durables, ***adoption growth***. The second is ***user growth***, representing the number of users over time, taking into account post-adoption churn. The final shape of interest is ***monetary growth***. Monetary growth is of particular relevance because it is at the core of managers' and investors' interest in XaaS markets. In some cases, the monetary growth analysis is based on the lifetime value that follows adoption, leading to measures such as CLV/CAC ratio (Ofek, Libai and Muller 2022). However, managers and finance professionals such as CFO's and other stakeholders (including venture capital analysts, consultants, and investors) are often interested in, and report, the period-by-period evolution of profitability over time (McCarthy, Fader and Hardie 2017; Skiera and Schultze

2014). Hence, period-by-period measures such as Annual Recurring Revenue (ARR), or its monthly equivalent MRR, have become essential analysis measures for XaaS firms.

The monetary growth analysis is thus built on the first two curves of the XaaS life cycle: either the adoption curve and customer lifetime value assessment or the user curve and the period-by-period margin. To understand this pattern, we need to understand the sequence from the adoption to the user and then the monetary curve. For example, we consider the case of Buzzers, who spread word of mouth about the new product. Buzzers can accelerate the adoption curve, which will affect the shape of the user curve, and, consequently, that of the monetary curve.

To apply the lifecycle approach to the growth of XaaS we are helped by a model adapted from the service diffusion model of Libai, Muller, and Peres (2009). We focus on the user and the monetary curves and provide several propositions regarding their shape and the factors that affect them. Both formal analytical examinations and simulations help us in this quest. Given the scope of the issue and the need to update the fundamental thinking on this critical area of research, it is only a first step in this direction.

The article proceeds as follows. We start by presenting the framework of the three-part XaaS life cycle analysis, followed by describing the model we use to demonstrate the patterns. Then, we derive several propositions regarding the shape of growth patterns and the role of the different curves of interest that illustrate the importance and potential of this framework. Looking at the number of users over time, we first examine how the user potential is affected by churn (Proposition 1), compare the peak in terms of the number of net users to that of net adopters (Proposition 2), investigate the effect of churn on the size and the timing of the peak of net users (Proposition 3), and how it is affected by the presence of pre-launch Buzzers (Proposition 4). We then look at the composition of the users and their sensitivity to churn (Proposition 5).

Table 1: Previous research on profitability in growing XaaS markets

Article	Focus of paper	Growth model	Attrition type	Main insights
Gupta, Lehmann & Stuart (2004)	Measuring customer equity of a growing product for customer-based valuation	Technological substitution logistic model - a simplified Bass model (without an external coefficient)	Fixed Lost-for-Good retention; Churn does not affect growth	Customer value provides a good proxy for firm value; Customer equity is highly sensitive to retention rate
Libai, Muller & Peres (2009)	Measuring customer equity of a growing firm that takes retention into account in both non-competitive and competitive cases; Comparing customer equity to market cap	Extended Bass model that includes retention in both category and brand level cases	Customers who churn join the pool of future adopters; Retention affects growth via a social process	Services growth should be modeled taking the effect of retention on growth into account and can serve as the basis for customer equity calculations; Customer equity assessments were generally close to stock market valuations
Schulze, Skiera & Wiesel (2012)	Linking customer and financial metrics to shareholder value via customer equity	Technological substitution logistic model (simplified Bass model)	Fixed Lost-for-Good retention; Churn affects growth	Debt and nonoperating assets impact the influence of customer equity on shareholder value; Support for infinite horizons in customer-based valuation models
McCarthy, Fader & Hardie (2017)	Using data from public financial reports for the valuation of subscription-based business	Time to adoption is modeled as a split-hazard model	Heterogenous dynamic Lost-for-Good retention	Public data can be used for customer-based valuation; There is a need to fully model the dynamics of acquisition and retention when valuing firms
McCarthy & Fader (2018)	Using data from public financial reports for the valuation of non-subscription-based business	Time to adoption is modeled as a mixture of hazard models	Repeat order timing model	The methodology suggested better predicts sales than alternative models; Noncontractual relationship value can be estimated based on public disclosures
Ben Rhouma & Zaccour (2018)	Optimizing customer acquisition and retention to maximize the customer equity of a growing firm	Simplified Libai Muller & Peres model (without contagion effects); The firm affects acquisition and retention	Customers who churn join the pool of future adopters; Retention affects growth	Optimal acquisition and retention investments are constant in the absence of contagion; Changing acquisition spending given contagion effects
Mesak Scott & Bari (2022)	The effects of marketing mix variables on subscription-based growth	Modified Libai, Muller & Peres model that considers advertising and price	As in Libai, Muller & Peres (2009)	Including marketing mix variables improves fit and predictive ability; Difference between the maturity and growth stages

Next, we focus on monetary growth and compare the consequences of using an ARR vs. CLV approach (Proposition 6) as well as how customer acquisition impacts the "trough" in the net monetary curve (Proposition 7). The concluding section highlights issues of interest in the XaaS lifecycle, including the covert and dynamic effects of churn, discusses the shift towards and the relevance of the increasingly popular measure of *net dollar retention*, and the role of marketing mix variables as well as competition in the XaaS lifecycle.

2. Customer Life Cycle and XaaS Growth

The XaaS Phenomenon

We begin by setting the boundaries for the new product or service phenomena we will examine: We consider any business as XaaS if it entails continuous recurring consumption activities by individuals following the adoption of a new product or service. Such customer relationships have sometimes been labeled as "contractual relationships" (Fader and Hardie 2015) or "subscriptions" (Ben McCarthy Fader and Hardie 2017; Ben Rhouma and Zaccour 2018) and apply to both B2C and B2B settings (Kowalkowski and Ulaga 2024). We prefer the more inclusive term "XaaS", because customers do not necessarily need a contract to be in a continuous relationship, such as in the case of continuously used games, and continuous customer relationships are not necessarily labeled "subscriptions," such as in a relationship with a bank. Practitioners often refer to Software as a Service (SaaS) in the context of growing digital products, yet the phenomenon is beyond mere software. Thus, the XaaS terminology offers a more holistic view (Bertini and Koenigsberg 2020).

De facto, the growing XaaS thinking we present here may also be relevant to noncontractual relationships where customers have an on-and-off relationship with the seller, and it is less clear when they leave (Fader and Hardie 2018). However, modeling such relationships is complex and requires additional assumptions. Here, we follow much of the previous literature on growing XaaS and focus on continuous relationships where churn can be identified.

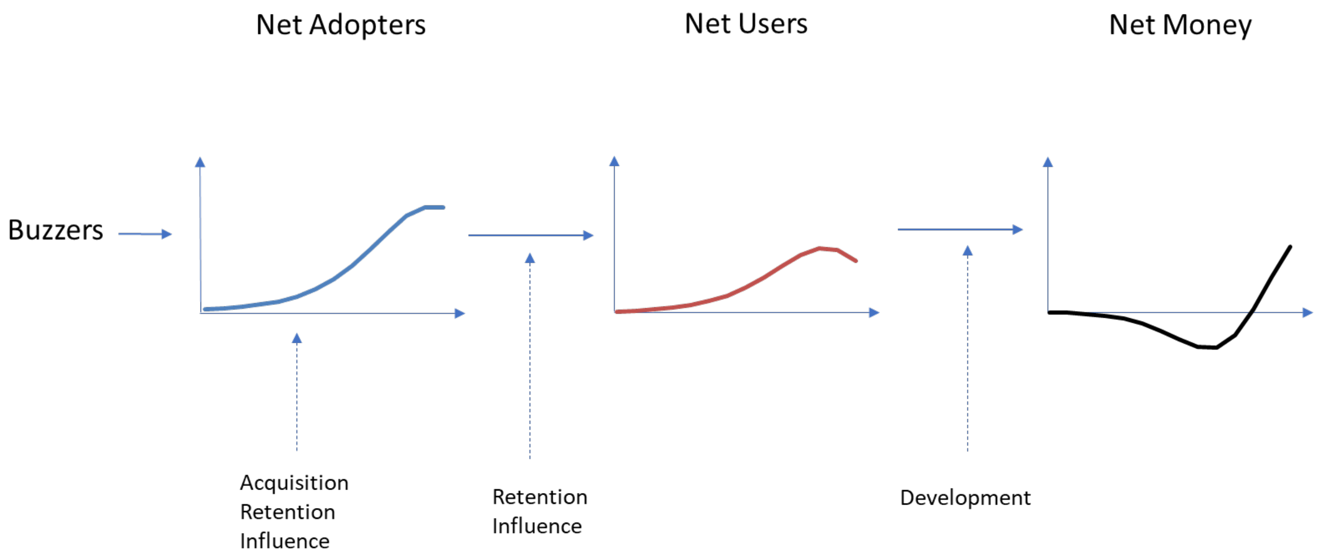
The Product and Customer Lifecycle

The Product Life Cycle (PLC) is a key framework for examining market growth and is an integral part of marketing textbooks (Kotler, Keller, and Chernev 2021). The theoretical base for the shape of the PLC has been primarily attributed to diffusion theory, which describes how innovations spread in a market (Golder and Tellis 2004). The quantitative analysis of product growth has been thus done mostly via diffusion models such as the Bass model and its extensions and other models that capture the bell-shaped nature of growth (Peres, Muller and Mahajan 2010; Meade and Islam 2006). XaaS growth also follows the lifecycle, including post-adoption behavior of recurring consumption relationship with the supplier. The customer relationship management literature has focused on how these recurring consumption relationships create profitability over time through customer lifetime value at the individual customer level and customer equity at the customer base level (Du et al 2021; Rust, Lemon, and Zeithaml 2004).

Customers create value for the firm through four types of behavior, which are sometimes labeled in practice as the Customer Life Cycle (Agility 2022; Saasquatch 2023): ***Join***: Customers buy the product for the first-time following customer acquisition efforts of the firm. Customer joining creates the adoption curve for new products. ***Grow***: Existing customers grow through customer development efforts: Cross-selling, up-selling, higher markup, and higher purchase frequency. ***Stay***: Customers stay longer and do not churn following customer retention efforts. ***Influence***: Customers influence other customers' joining, growing, and staying. This behavior can be affected by the firm's influence management efforts.

The growth of XaaS products is thus a combination of the *product life cycle* in which the XaaS product is first adopted and the *customer life cycle*, which affects the product life cycle and creates profitability over time. Importantly, influence can happen at any XaaS life cycle stage. The value chain is demonstrated in Figure 1:

Figure 1: XaaS Value Chain



Net Adopters Growth: In Figure 1, the firm's customer acquisition efforts naturally affect the adoption growth. Yet, it is also impacted by social influence from previous adopters through word of mouth, observational learning and norms, as well as network externalities (Peres, Muller and Mahajan 2010). Due to the social impact, customer retention efforts will also affect adoption: When people disadopt, the number of previous adopters that can influence prospective adopters goes down, which will affect the speed of adoption (Hogan, Lemon and Libai 2003).

An interesting effect to consider is that of pre-launch social interactions. While historically, diffusion models have assumed that social influence starts with the launch of new products, there is a growing realization of the importance of the buzz process before new products are launched, amplified by the availability of communication via social media

(Gelper, Peres, and Eliashberg 2018). The effect of ***buzzers*** who are individuals who spread information and "buzz" about the new product before the launch of the product, can be substantial. It implies that at product launch a mass of individuals will adopt it early on, not requiring a gradual social influence process that can result in a long left-tail. This may strongly affect the adoption curve.

Net Users growth: We distinguish between the user base, the current number of active users, and its change over time, which we label *net users*. The latter's growth is based on adoption growth and thus is influenced by the factors that affect adoption growth. However, it is further impacted by customer retention since only some of the adopters stay as users. The number of users at each point in time is a function of the size of previous cohorts and the time that has elapsed since they adopted the service. Social influence can also play an indirect role since the churn decisions of individuals are affected by their environment, particularly the churn decisions of others (Landsman and Nitzan 2020; Moldovan et al. 2017). Therefore, retention affects the user curve in two ways: first, it affects the shape of the adoption curve, and then, it affects the transition from adoption to usage.

Money growth: Lastly, in converting users into money, particular attention should be given to the temporal role of costs. The ARR growth curve often represents the monetary curve in practice (Parative 2024). However, it does not consider customer acquisition costs, which may bias the picture of cash flow for the firm. The *net monetary curve* that considers CAC may be better suited for a more complete view. For this curve, one should also consider that the average revenue per user (ARPU) may change over time. For example, ARPU may decline over time due to satiation (Haenlein, Libai and Muller 2023) or increase due to the *development* of the user base following actions such as cross-selling and upselling (Due et al. 2021). The transition from the user curve to the monetary curve may thus not be straightforward.

3. Modeling XaaS growth

In order to conduct a more detailed analysis of XaaS growth, let's consider the case of the media streaming company Roku (www.roku.com). Roku's business model illustrates the shift from traditional durable goods to XaaS: Consumers purchase the Roku streaming device and, using their home network, can stream TV shows and movies from various providers such as Netflix, purchase TV shows, and are exposed to advertising messages. Typically, a user starts by acquiring the hardware and then transitions to post-adoption behavior, which includes paying for channels and subscriptions. According to the 2023 data, Roku's revenues from hardware sales were approximately $490 million, while post-adoption sales, predominantly from advertising, totaled about $3 billion. This indicates that for every dollar Roku earns from hardware sales, it gains more than six times that amount from its services (Roku 2023 Annual Report, p. 57). A key factor in the growth of Roku's user base, as opposed to just hardware adopters, is the churn rate. Table 2 presents the number of Roku users – those using the streaming service – and the number of new hardware adopters. To understand Table 2, it's important to define certain terms that are essential to the XaaS growth model[1]:

- **Adopters** – $a(t)$ – number of cumulative adopters as in the classic diffusion of innovation literature.
- **Net Adopters** – da/dt – change in the number of adopters over time.
- **Users** – $x(t)$ – number of users over time, sometimes referred to as user base.
- **Net Users** – dx/dt – change in the number of users over time.

Finally, let δ be the post-adoption churn rate. Given these definitions, the relation between new adopters and new users is given by Equation 1:

(1) $da/dt = dx/dt + \delta x$

[1] Note that both dx/dt and da/dt could be written as $x_{t+1} - x_t$ and $a_{t+1} - a_t$ in the discrete time version.

Table 2: Users and adopters of Roku streaming service, world-wide, 2023*

	Roku active users at the end of the year (in thousands)	
2023	x_{t+1}	80,000
2022	x_t	70,000
Net addition (net users)	$x_{t+1} - x_t$	10,000
Churn	δx_t ($\delta = 20\%$[2])	14,000
Actual number of new adopters in 2023 (net adopters)	$x_{t+1} - x_t + \delta x_t$	24,000

* Source: Roku 2023 annual report

Note that the net addition to the number of Roku users (net users) in 2023 is 10m. However, during this year, a total of 14m users left the service, as the churn rate is about 20%. Thus during 2023, about 24m new customers bought the Roku hardware device. Yet if we count the number of users, who contribute the majority of Rokus revenues (86% to be precise), only 10m new users were added during this year. Figure 2 shows the estimated Equation (2) from its inception for Roku's net subscribers and new adopters.

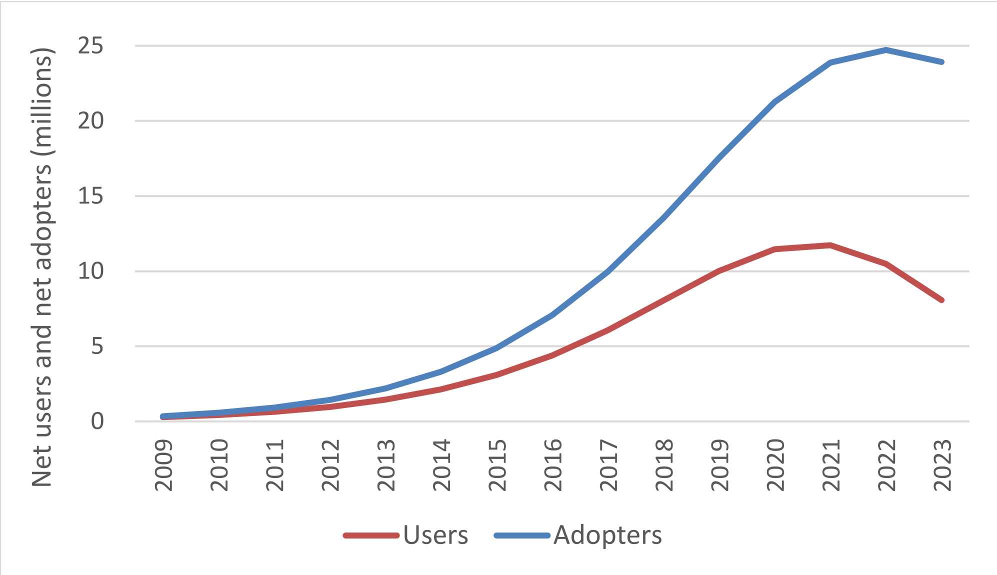
Figure 2 tells two interesting tales: First, the number of adopters of Roku's streamer is much larger than the number of users of the service Roku provides. Estimating and predicting these figures are essential for various reasons, including production, logistics, marketing, and price negotiations for ad-supported streaming. Second, the peak of the number of new adopters (2022) is ***later*** than the peak of the number of new users (2021). We subsequently show that this is a general case and not specific to this dataset and that this difference increases with increasing churn.

While Roku is a good example to highlight the transition from products to XaaS, most XaaS growth patterns, such as those of many direct-to-consumer subscription firms, do not

[2] The churn rate is our own conservative estimate as it does not appear in Roku's annual report – see our discussion on this point in the last section.

include a durable part. As the durable part is well-known and heavily researched, we next focus on pure XaaS growth. To do so, we first need to specify the model used to describe users' growth.

Figure 2: Growth of the number of Roku's net users and net adopters (in millions)*



* Source: Roku annual reports and Statista

As seen from Table 1, the growth of XaaS can be modeled using various combinations of growth functions and customer relationship structures, particularly the type of churn. Our aim here is not to suggest a new modeling approach but to focus on how the XaaS lifecycle is created via the three curves of interest. We follow Libai, Muller, and Peres (2009), which has been the base for other modeling approaches in this area (Mesak Scott, and Bari 2022). Similar to other work in this area, this model has been used for valuation rather than to examine the nature and shape of growth of users and adopters.

Libai, Muller, and Peres (2009) consider customer churn to be an integral part of the growth process[3]. The modeling framework suggests that when users churn, they return to the potential customer pool where they may later re-adopt. The model is given by:

$$(2)\ \frac{dx}{dt} = \left(p + \frac{qx}{m}\right)(m - x) - \delta x$$

In this equation, p is the external coefficient such as advertising, q is the internal coefficient such as word of mouth and other contagion mechanisms or network effects, m is the market potential, and δ is the churn rate. Libai, Muller and Peres (2009) showed that this model is equivalent to the Bass model with new parameters (these parameters are now converted to the simpler model), that is, the solution of Equation 2 is given by Equation 3[4]:

$$(3)\ x(t) = \bar{m} \cdot F(t) = \bar{m} \cdot \frac{1 - e^{-(\bar{p} + \bar{q})t}}{1 + (\bar{q}/\bar{p}) \cdot e^{-(\bar{p} + \bar{q})t}}$$

In this equation, $F(t)$ is the fraction of the effective user potential that are current users at time t. The parameters of the new growth, represented by Equation 3, are given by the effective external coefficient $\bar{p}$, the effective contagion parameter $\bar{q}$, and the user potential $\bar{m}$:

$$(4)\ \bar{p} = (\Delta - \beta)/2$$

$$(5)\ \bar{q} = (\Delta + \beta)/2$$

$$(6)\ \bar{m} = m(\Delta + \beta)/(2q)$$

$$(7)\ \beta = q - p - \delta$$

$$(8)\ \Delta = \sqrt{\beta^2 + 4qp}$$

[3] The model we use is a slightly modified version of the one by Libai, Muller, and Peres (2009) without the term (1-δ) in the contagion coefficient q. The reason we can use the simplified version is that, as the authors show in the web appendix to their paper, the models with and without this term are precisely equivalent. Therefore, the use of the simpler model is warranted.

[4] Note that we need $\bar{p}$ and $\bar{q}$ only for demonstrating the similarity of Equation 3 to a Bass process. In Appendix A we show the solution without referring to these two constructs.

4. The growth and composition of users

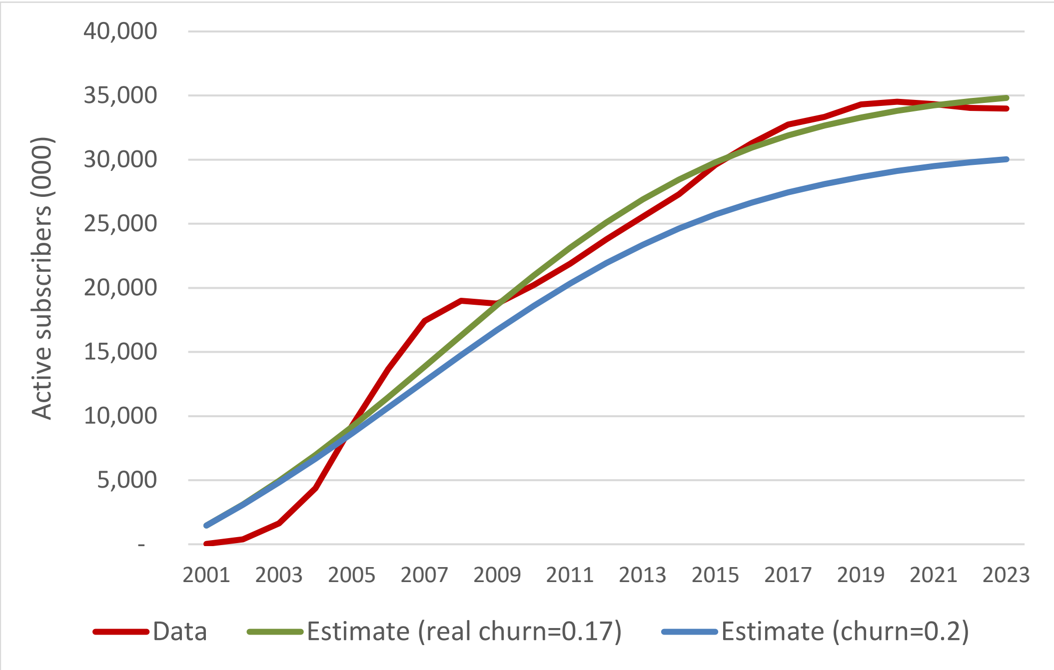
While the adopter growth patterns have been much analyzed in the diffusion literature, we have limited intuition on the users' and net users' curve patterns. In this section, we explore the adopter curves, postulate several propositions regarding their patterns and test them. To do so, we use both analytical proofs and simulations. For all the simulations, we define the parameters of interest with diffusion parameters in the range $0.001 \leq p \leq 0.07$, and $0.2 \leq q \leq 0.8$, consistent with the ranges observed in the new product literature (Chandrasekaran and Tellis 2018). We define the churn rate range of $0.05 \leq \delta \leq 0.5$ which is a wide range in which the firm can lose from 5% to 50% of users in a period. As the propositions we are testing via simulations do not depend on the market potential m, we fix m at 1,000 for convenience.

The user potential

Given that user growth can be described with a Bass-type process as per Equation 3, it follows that the user curve is S-shaped or concave, where the asymptote of the curve is the "market potential" in the classical diffusion nomenclature. In the XaaS growth model, the number of users will increase with time until it reaches an asymptotic equilibrium in which the number of adopters from the remaining potential pool equals the number of users that churn. We term this potential the "user potential," corresponding to the maximum number of users. As an example, consider the growth of the number of subscribers of SiriusXM Satellite Radio in the last 20 years in Figure 3. Three noteworthy comments regarding the user potential in general using the example of SiriusXM Satellite Radio:

First, the user potential is the user base - $x(t)$, that is s-shaped, yet it can decline temporarily. This is an important difference from the classic economy with sales of durables. Different reasons such as a recession can affect current sales, but it cannot affect cumulative adoption by definition: Cumulative adoption $x(t)$ of durables adds all previous adopters and thus cannot decline. In the XaaS framework, $x(t)$ is the user base but it can decline for several reasons, such as an economic downturn, a sudden increase in churn, or just bad publicity with the brand. Note that we have modeled a constant churn for simplicity, but a dynamic churn and a dummy variable for the economic conditions could be added to the equation[5]. In Figure 3, we see two such occurrences in 2008-2009 and 2021-2022; both occur because satellite radio is highly correlated with car ownership, and in these periods, car sales and ownership were negatively affected by external events.

Figure 3: SiriusXM Satellite Radio users (active subscribers in thousands)*



* Source: Annual reports of XM, Sirius and SiriusXM

Second, as can be seen from Figure 3 in our example users have hovered just below 35m in the last four years. Just eyeballing the figure, this seems to be the effective user potential of SiriusXM. Indeed, if we estimate the model given by Equations 2 and 3 on SiriusXM data, the users' potential $\overline{m}$ can be computed (via Equation 6) to be 35.7m users. Of course, many

[5] We examine the effects of dynamic churn in the discussion section.

more cars are registered in the US (about 290 million), but what the data reveal is that SiriusXM has reached its user potential at around 36m, or equivalently, that only one in eight vehicles is ever likely to have a satellite radio installed and active.

Third, while the actual annual churn rate in the case of SiriusXM is 17%, what would happen if it increased to 20%, ceteris paribus? As shown in Figure 3, the churn rate determines the size of the user potential compared to the market potential for durables with the same growth parameters. If the churn rate is zero, the user potential is the market potential of all users. As the churn rate grows, the market potential will not be realized, and the asymptote will be in a lower magnitude. This general case which differs from the market potential for durables is summarized in the next proposition and proven analytically in Appendix A.

Proposition 1: User potential declines with an increase in churn.

This result has significant implications for the firm's growth and financial performance, as shown in the next section. In Figure 3 we present the hypothetical case of an increase of the churn rate of SiriusXM from the current 17% to 20%. This increase of about 20% would result in a decrease of about 14% in the user potential, from 36m to 31m, which is quite a significant drop. To get a better intuition for the general case, Table 3 summarizes how a 20% change in churn rate affects user potential in selected XaaS firms.

Table 3: Churn rate and user potentials in selected XaaS firms*

XaaS Firm	Current churn rate	Current User Potential (million users)	New Churn rate (20% higher)	New User Potential (million users)
Peloton	13.5%	3.4	16.2%	3.3
Roku	20.0%	91	24.0%	84
SiriusXM	17.0%	36	20.4%	31
Spotify (premium)	17.9%	279	21.5%	255

* Sources: Annual reports of Peloton, Roku, SiriusXM, and Spotify; and Statista

Note that for the small firms such as Peloton, this does not appear dramatic at first, yet this increase in churn does have a significant effect on the user potential. Take Roku as an example: An increase of churn from the current 20% to 24% reduces the user potential by 7 million users from its current 91m user potential. These are 7 million potential users that Roku will never see, nor enjoy their lifetime value, regardless of their expected retention rate and viewing habits.

The peak of net users

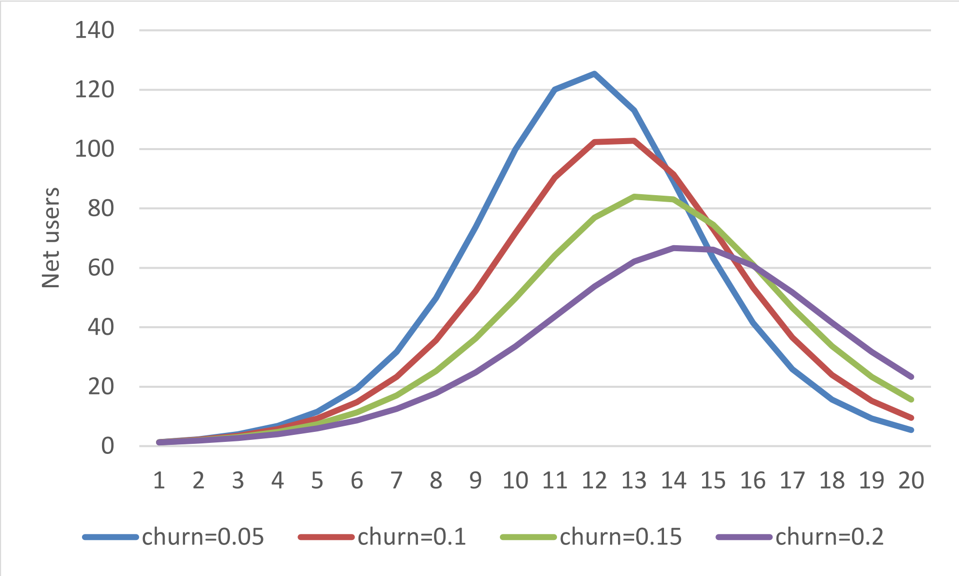
The equivalent to the new adopter curve is the *net user curve* which represents the number of new adopters minus churning customers. It is straightforward to see that the net user curve is also bell-shaped, like the new adopter curve. However, the exact shape will differ. To see that, we examine the peak of the net user curve. The peak of sales is recognized as a key performance measure for firms, particularly the time to peak and its size (Fischer, Leeflang, and Verhoef 2010). However, while the peak in the classic adopter curve has been studied (Mahajan, Muller, and Srivastava 1990), it is not the case for the peak of net users.

Recall the finding of Figure 2 that the peak in the number of Roku's net adopters (2021) is ***later*** than the peak in the number of new users (2020). We argue that it is not specific to Roku, as demonstrated in the next proposition, and proven in Appendix A.

Proposition 2: The peak of the number of net adopters is ***later*** than the peak of the number of net users.

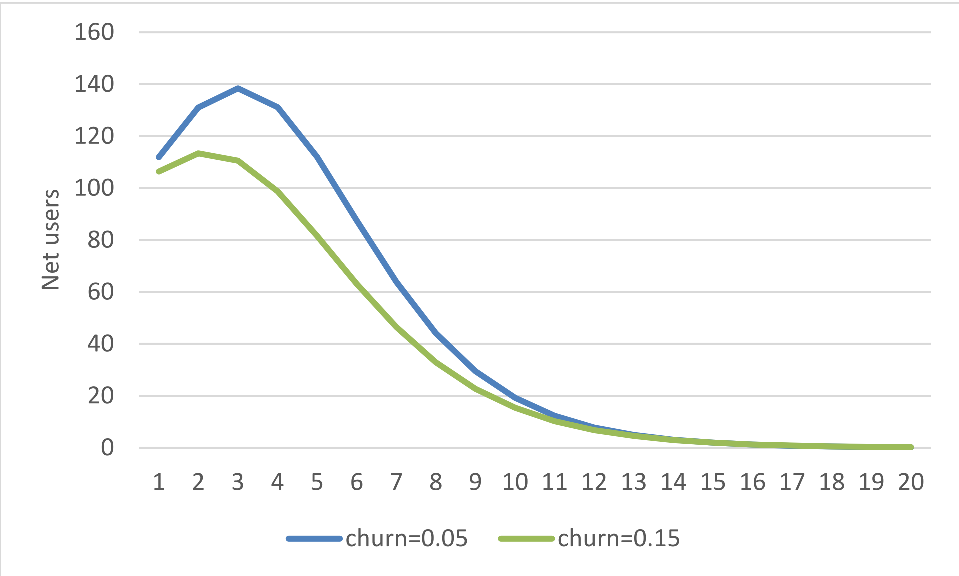
This result may seem counterintuitive as adoption is a prerequisite for usage. But it can be explained by Equation 1. When the maximum of net users is reached, the number of net adopters is still increasing, and thus, though it is larger in absolute terms, in terms of speed, it actually lags behind the number of net users. To further look at the net user curve, consider Figure 4, in which we observe the growth curves of net users for various churn rates.

Figure 4: Growth of net users for various churn rates*



* Source: Simulations of Equations 2 & 3: $p = 0.01, q = 0.6, m = 1{,}000$

Figure 5: Early skewed growth of net users for two churn rates*



* Source: Simulations of Equations 2 & 3: $p = 0.1, q = 0.4, m = 1{,}000$

We observe a decline in the peak of net users and an increase in the time at which this peak is achieved. The significant drop in the peak number of new users in Figure 4 is driven by two forces: First, a decline in the fraction of new users when churn increases, and second, a corresponding decline in the user potential. However, this can be reversed with early skewed growth in the fraction of new users, as is depicted in Figure 5[6]:

Figure 5 tells a counterintuitive story: For early skewed growth patterns, higher churn leads to an earlier peak. The reason is that the effective external and internal coefficients are functions of churn. In the context of symmetric growth, the external parameter slightly increases with churn while the contagion coefficient sharply declines, thus leading to the pattern of Figure 4. However, with a large external coefficient necessary for early skewed growth, this pattern reverses, and the contagion coefficient slightly declines. However, when the external coefficient sharply increases, it leads to the pattern of Figure 5. We summarize these findings by the following proposition:

Proposition 3: With increased churn, the peak in net users decreases, while the time to peak generally increases. However, for early skewed growth, the time to peak might decrease.

As we show in Web Appendix B, in our simulations, the level of peak declines with an increase in churn. In 88% - hence most cases - an increase in churn increases the time to peak. In the remaining 12% of the cases, the time to peak decreases due to two reasons: Either due to an early skewed process as depicted in Figure 4, or due to a very low number of active users, i.e., the curve becomes flat, and the time to peak becomes relatively unstable and can therefore decrease.

Buzzers and the declining adoption curve

It has been widely accepted across disciplines that the adoption curve is expected to bell-shaped for new products (a symmetric one according to the Bass model), and the cumulative adoption curve is S-shaped (Rogers 2003; Meade and Islam 2006). Yet in certain markets,

[6] We refer to a curve to be early skewed if its peak is earlier than a symmetric function (counterintuitively called right skewed in statistics). Note that proposition 3 does not indicate that time to peak declines for all early skewed growth processes.

such as the entertainment industry, it has been observed that the adoption curve can instead monotonically decline over time, resembling an exponential decay (Foutz 2017). In the movie industry, for instance, this trend can be attributed to the producers' strategy of promoting the film before its launch to generate buzz. This pre-release buzz, coupled with the wide availability of screenings upon release and the viewers' inclination to be the first to see the movie, often leads to an initial surge in demand.

The case of movies can be seen as only part of a broader phenomenon that affects the user curve. Classic diffusion modeling assumes that social influence (word of mouth, imitation, or network effects) starts when the product is launched. It creates the left tail, leading to the adoption curve bell shape (Rogers 2003). However, we see increasing evidence where the social influence part of the customer life cycle precedes initial acquisition. Online sources, particularly social media outlets, enable users to be exposed to information, discuss, and create social influence before launching a new product (Gelper, Peres, and Eliashberg 2018). Firms take advantage of that and pre-announce products (Zhang and Choi 2018) and allow pre-ordering that will materialize when the new product is launched (Moe and Fader 2002).

When this happens, many customers will adopt the product as it is launched. This will affect the adoption curve and, consequently, the user curve. To show the basic effect of this phenomenon we do not get into the dynamics of the social influence process, but lump all forms of pre-launch social influence under "buzzers". The larger the number and persuasiveness of buzzers, the larger is the mass of the adopters at launch. This has consequences for the user curve.

The following proposition implies that the larger is the number of adopters at the beginning of the process, the more the user curve will be early skewed to the point that it might begin with a decline rather than an increase in the number of users. As we show in

Web Appendix B, the following proposition holds for all values in the range of parameters in our simulations.

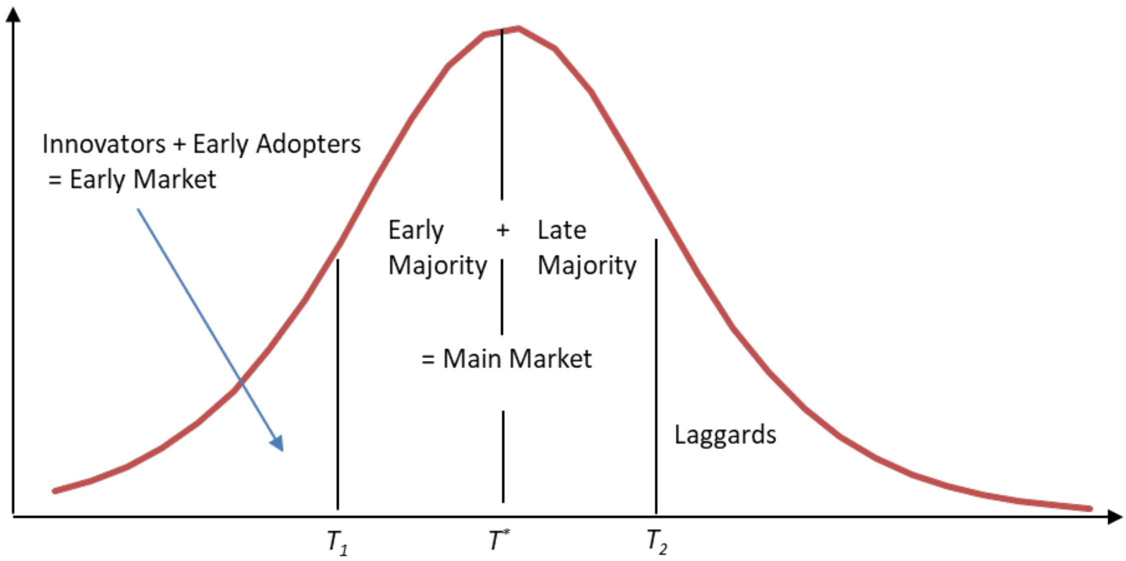
Proposition 4: With an increase in the effect of buzzers, the time to peak of net users declines, and above a certain threshold, the net user curve is monotonically decreasing.

Composition of users

In light of the focus of traditional new product frameworks on first adoption, the move to XaaS thinking might require updating the fundamental thoughts on the diffusion of innovations. A relevant example are the adopter categories, which are often used for segmentation and are an integral part of marketing textbooks: While the traditional breakdown of adopters to innovators, early and late majority and laggards have theoretical as well as empirical support (Rogers 2003; Mahajan Muller and Srivastava 1990, Appel and Muller 2021), current thinking leans towards a simpler yet managerially relevant segmentation, of just two segments: early and main market (Lehmann and Esteban-Bravo 2006, Muller and Yogev 2006, Van den Bulte and Joshi 2007), as depicted in Figure 6:

In the XaaS context, we can ask an analogous question: what is the proportion, of users belonging to each segment based on the first time they used the service? We use the Appel and Muller (2021) and Mahajan, Muller and Srivastava (1990) frameworks and define the innovators and early adopters as the early market while the majority (early and late) as the main market. Both are based on the two inflection points of the diffusion curve: Early market size is the area under the growth curve from zero to the first inflection point, while the main market is from the first to the second inflection point.

Figure 6: Adopter Categories



We find that with an increase in churn, the relative size of the early market declines while the relative size of the main market increases, as per the following proposition (see Appendix A for a proof):

Proposition 5: With an increase in churn, the relative size of the early market declines, while the relative size of main market increases.

The intuition behind the result is based on the growth curves in Figure 4: It's apparent that the high churn rate figures are not only late in achieving the peak, but also the second inflection point is later, causing the main market to increase. Thus, analyses of segmentation prediction and optimal market behavior that have been based on first-adoption thinking should be re-considered for the case of the growth of XaaS.

5. Monetizing users

Investors' and managers' interest in XaaS growth stems from their desire to comprehend the temporal financial benefits generated by the venture. There are two essential methods to evaluate monetary creation over time. The first, known as the Annual Recurring Revenue approach (ARR, or its monthly equivalent MRR) relies on the user curve, considering the revenue changes from one period to the next. In essence, it is the firm's revenue that is expected to continue in the future. These revenues are predictable and can be counted on to occur at regular future intervals (Liberto 2022, Palmer 2021)[7].

The alternative method is the Customer Lifetime Value (CLV) approach, which focuses on adoption rather than user numbers. For each new adopter, the customer lifetime value is estimated at the point of adoption or averaged across a cohort in the discrete version (Gupta, Lehmann, and Stewart 2004; Libai, Muller, and Peres 2009). As the number of adopters increase, the monetary curve shows the accumulation of long-term value over time. The CLV approach forms the basis for measures like Unit Economics (CLV/CAC), which is commonly used to assess the success of new technological ventures (Ofek, Libai and Muller 2022).

Despite their difference, both methodologies underscore the importance of comprehending the adoption and user curve. Scholars advocating long-term analyses that support optimal firm decision-making typically favor the CLV approach (Schulze, Skiera, and Wiesel 2012), especially in marketing (Skiera and Schultze 2014). Conversely, the ARR approach tends to be preferred by investors and practitioners, especially finance executives, who are often concerned about resource availability and may hesitate to measure success based on yet-to-materialize long-term indicators (McCarthy, Fader and Hardie 2017). However, the necessity to consider long-term profitability in firm valuation, thus utilizing CLV and Unit Economics, is also acknowledged. In practice, business literature often suggests employing both measures, yet it generally falls short in discussing the biases and disparate results that can arise from using different methods (Sacks and Ruby 2021).

[7] Note that ARR refers to revenues while customer equity, which is the subject of the first part of this section, deals with gross profits.

__Customer equity under the two approaches: ARR and CLV__

Customer equity is the net present value of future earnings from customers. It is considered by many as the ultimate measure to assess the success of the firm: The actions the firm takes and the tradeoff it makes should be judged through the lens of the effect on customer equity (Kumar and Shah 2008; Villanueva and Hanssens 2008, Skiera and Schultze 2014). We thus ask first whether the two approaches yield a similar customer equity assessment. To do the calculation, we consider both the users' margin per period (revenue minus the appropriate costs to serve and retain the user) and the acquisition costs of new users. Consistent with our previous notations, let $x(t)$ be the number of users at time *t*, da/dt - the number of new adopters at period *t*, g is the margin per customer per period, *i* denotes the cost of capital of the firm (WACC), *CAC* is the customer acquisition costs and δ is the churn rate. We use a formulation of $CLV = g/(i + \delta)$ as in the standard approach.

The two methods present simple ways to measure the equity of a firm: The CLV method (Equation 9) takes the number of ***new adopters*** at each period and multiplies it by the CLV of each new adopter minus the cost of acquiring this user. This is as similar as it could be to the old way to measure equity: Take the number of buyers of a durable such as a TV set and multiply it by its price (minus costs).

$$\text{(9) CLV Based Customer Equity} = \int_0^\infty (CLV - CAC) \cdot \frac{da}{dt} \cdot e^{-it} dt$$

Annual recurring revenue is defined as either average revenue per user (ARPU) multiplied by the number of current users (Liberto 2021), or, equivalently as ARPU multiplied by the number of customers of the last period, plus new adopters, minus churning customers (Salesforce 2023). Thus $\text{ARR} = \text{ARPU} \cdot x(t)$. Two modifications are required for this analysis: First, ARR usually considers changes in ARPU, while we assume, as is the standard in customer equity calculations, a constant ARPU and costs[8]. Second, to calculate equity, we subtract the average customer service costs and, therefore, define the gross profit margin (*g*) as APRU net of average costs.

Thus, the ARR method (Equation 10) takes the number of ***users*** of the XaaS firm and multiplies each by the unit gross profit margin of the service minus the cost of acquiring the new adopters (CAC). In both cases, to derive the customer equity, one computes the NPV of these streams using the firm's cost of capital. What we show next is that the two approaches yield equivalent measures for the infinite horizon case yet not in fixed periods (See Appendix A for an analytical proof):

$$(10)\ \text{ARR Based Customer Equity} = \int_0^\infty \left(g \cdot x(t) - CAC \cdot \frac{da}{dt}\right) \cdot e^{-it} dt$$

Proposition 6a: With an infinite horizon, the ARR and CLV based customer equity yield the same result, that is Equations 9 and 10 are equivalent.

Proposition 6b: With a finite horizon, the CLV methods yields a higher value than the ARR approach that more accurately reflects the true customer equity.

In the traditional infinite perspective, it becomes evident that, irrespective of the approach used to analyze the revenue stream, the results are identical. This is because the underlying data in both cases is a matrix representing the revenues (or profits) for each cohort in each time period. If we sum the rows, we obtain the cohort-by-cohort view. If we sum the columns, we acquire the period-by-period view. If the underlying matrix is the same, both views must yield the same valuation[9]. However, investors and firms may not always work within an infinite timeframe; instead, they focus on customer profitability over a defined number of years. Within the context of a specified timeframe, differences between the

[8] In the next section we deal with the more complex case of dynamic churn.

[9] For more on this see Skiera and Schulze (2014), and McCarthey, Fader and Hardie (2017).

methodologies begin to emerge. Even when the number of cohorts under scrutiny is limited, the CLV approach, typically built on long-term calculations, captures a greater portion of infinite customer equity compared to the ARR approach. Given the vital role of customer equity in a firm's valuation (Schulze, Skiera, and Wiesel 2012, Wiesel, Skiera and Villanueva 2008, Skiera and Schultze 2014), this difference should be of much interest.

The net money growth

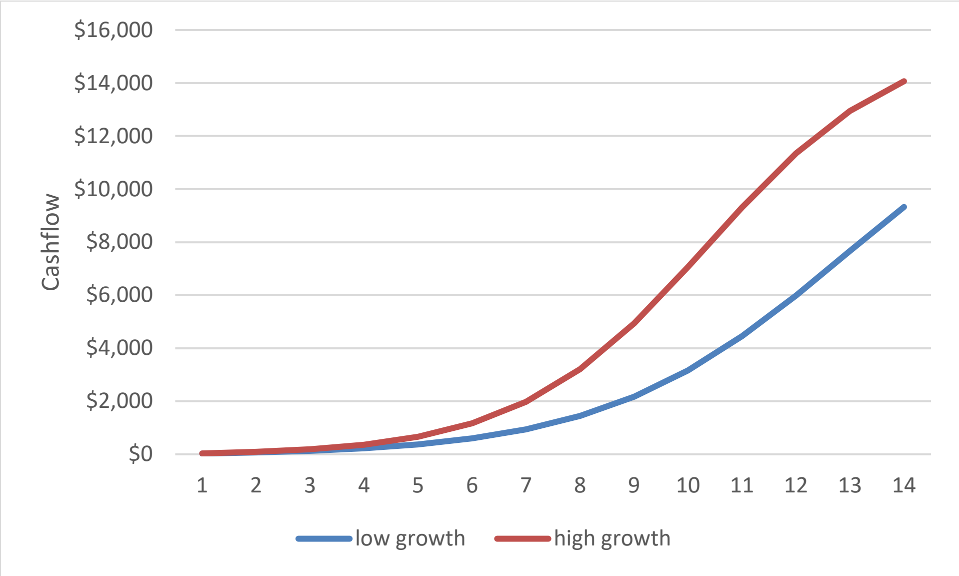
Examining the shape of the monetary curve, the scenario under the CLV approach is relatively straightforward. The net profit from a potential customer (customer lifetime value minus acquisition costs) is multiplied by the adopter curve. Consequently, the monetary curve will follow the shape of the adopter curve, albeit on a different scale. The scenario for the ARR approach is more complex. Standard industry practices for subscription firms often emphasize recurring customer revenue, excluding customer acquisition costs (Paddle 2023). The number of users will be multiplied by the average recurring revenue (or, more accurately, recurring margins) for each period. Assuming fixed parameters over time, in this case, the monetary ARR curves will resemble the user curve, again on a different scale.

However, if customer acquisition costs are factored in - a step necessary for a comprehensive monetary view - the shape of the curve can undergo a fundamental change. This is due to the possibility of several periods passing before the recovery of acquisition costs. As more customers are acquired, the firm incurs significant acquisition costs in the short run, which will only be offset in later periods.

Consider, for instance, a new subscription business with customer acquisition costs of $60, and an annual subscription margin of approximately $20. With a churn rate of 15% and a discount rate of 10%, the CLV is $80, leading to Unit Economics of 1.33 (80/20). However, as it is a new service, the number of new customers increases over time, with the rate of growth captured by the diffusion parameters. The firm contemplates two scenarios. Under the current "low growth" scenario, the growth parameters are $p = 0.001$ and $q = 0.6$. If the marketing department successfully boosts growth to a "high growth" scenario, the firm anticipates a 20% increase in both p and q. Ignoring customer acquisition costs and using the XaaS model growth, we can observe in Figure 7a the recurring margin over time for both scenarios. As expected, the high growth scenario appears more favorable. However, the picture is different when customer acquisition costs are taken into account. Looking at the low growth scenario, the cash flow is initially negative. Only after 14 periods it becomes positive. But the picture is more extreme in the case of the fast growth. While the point of positive cash flow is earlier, and later growth is faster, the initial losses are much larger. It is also clear that the overall loss before the firm reaches positive cashflow is larger for the fast grow scenario compared to the low growth scenario.

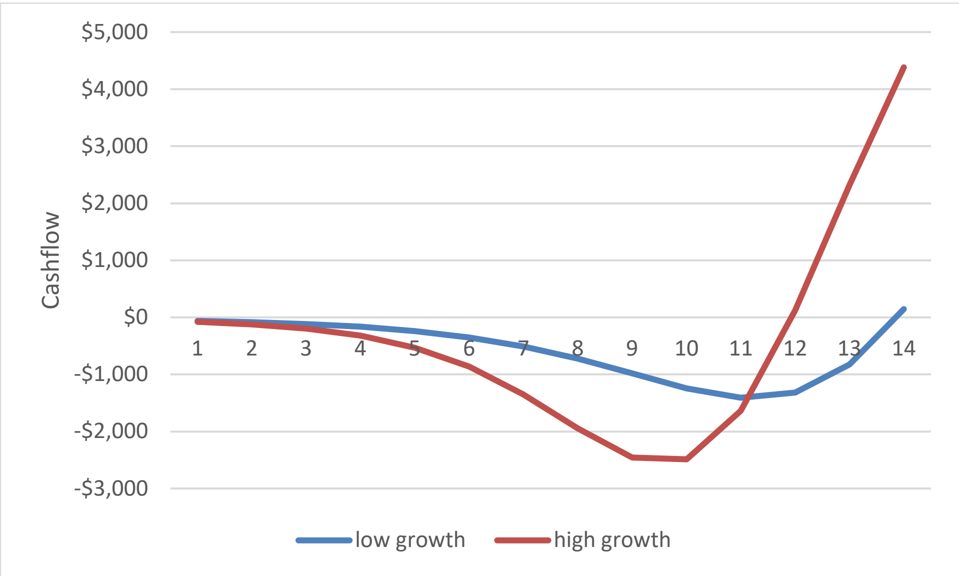
Define the ***cashflow trough*** as the maximum negative cashflow of the new venture (Skok 2017). For example, in the simulation leading to Figure 7b, the maximum negative cashflow of the fast growth is $2,488, while the corresponding one in the slow growth is only $1,408. Skok argues that for a fast-growing XaaS product, its managers often are not aware of the extent that faster growth will have on the depth of the trough. To generalize this point, we ran a simulation (Web Appendix B) where we changed the various profitability and growth parameters in the previously defined ranges. We demonstrate that faster customer acquisition increases the magnitude of the cashflow through. Hence proposition 7.

Figure 7a: Two cashflow scenarios without customer acquisition costs*



* Source: Simulations, CAC $= \$0, p = 0.001, q = 0.6, m = 1{,}000, g = \$20, i = 0.1, \delta = 0.15$

Figure 7b: Two cashflow scenarios with customer acquisition costs*



* Source: Simulations, CAC $= \$60, p = 0.001, q = 0.6, m = 1{,}000, g = \$20, i = 0.1, \delta = 0.15$

Proposition 7: Faster customer acquisition causes the magnitude of the cash flow trough, that is, the maximum negative cash flow, to become more negative.

Note that the situation we examine does not require the financial expenditures of fixed costs. It stems only from the XaaS-based framework, where the acquisition costs are paid upfront while the revenue stream trickles in later. Spending on fixed costs will only exacerbate the issue even further.

The trough example demonstrates the need for caution when moving from the user curve to the monetary curve and, more generally, the need to understand the three curves of the XaaS life cycle when analyzing growth. Multiplying the user curve in margin per customer and neglecting CAC (as often happens) may surprise investors and managers. Such a deep trough calls for larger cash reserves for the high growth firm over and above what is needed in marketing expenses to sustain this growth in a non-XaaS market. It also emphasizes the need to consider both types of monetary patterns. The CLV approach is intuitive and provides a closer estimate of the long-run customer equity. However, the focus on long-run customer equity disregards the short-run monetary pressure on firms, which is vital, especially for new ventures.

6. Discussion

The relevance and significance of the topics addressed above, is reflected in a critical question that investors and managers of XaaS ventures grapple with: the balance between growth and profitability. Prioritization of either approach has been revised multiple times, with no definite conclusion reached. While several years ago, managers were urged to prioritize growth at the expense of customer profitability (Mankins, 2017), more recently, the focus has shifted toward customer profitability (Heim, 2022; Harrington, 2022), but reports suggest a possible return to prioritizing growth (Wilhelm, 2023).

This growth-profitability conundrum is fundamentally tied to assumptions about the benefits of early market capture and its long-term impact on profitability. Nonetheless, the measurement and analytical structures must allow for comparability, transparency, and comprehensive quantitative analyses. We propose that the XaaS growth framework offers an appropriate blueprint. The central issue is maximizing customer equity, with different strategies that could rely on either the Annual Recurring Revenue (ARR) or Customer Lifetime Value (CLV) - both rooted in the adoption and user curve.

Within this context, it is crucial to acknowledge the financial limitations of new ventures and the reality of scarce resources, which may impede the implementation of an optimal strategy. While a CLV-centric approach aligns with long-term economic planning, recurring metrics like ARR cater to investors' interest in short-term analyses. This consideration is particularly critical given new ventures' limited resources and the need to demonstrate product-market fit to secure further funding (Georgiadis 2023). Digital insurance venture Lemonade serves as a pertinent case for this point. Lemonade reports a unit economics (CLV/CAC) ratio of three, indicating a strong standing from a CLV perspective. However, customer acquisition costs still pose a significant short-term challenge. To offset this liability, Lemonade partnered with an investment firm that now covers 80% of customer acquisition costs in exchange for a future return from the customers' lifetime value (Yahoo Finance, 2023).

Analyzing the benefits of such a scenario for Lemonade, or any similar XaaS growth firm, requires an in-depth understanding of the three XaaS growth curves - adoption, users, and monetary. The propositions detailed above addressing curve inflection points, the impact of buzzers and churn, and diverse monetary strategies can provide valuable insights for such analyses. Further research is necessary to offer broader generalizations on XaaS growth that will aid managers and investors in similar circumstances.

The covert effect of churn

The pivotal role of customer churn on the profitability of new XaaS products is clear. In the context of the growth-profitability tradeoff, the impact of churn on profitability, particularly customer lifetime value, has been recognized (Ascarza et al. 2018). However, churn also influences the adopter and user curves due to its effect on the social process, making the assessment of churn's impact on profitability more complex than often perceived.

Therefore, when adopters churn, there are two primary financial repercussions due to churn's influence on customer equity: The **overt direct churn effect** pertains to the loss of cash flows from the departing individual customer. This effect is deemed 'overt' as it's immediately visible to the firm - a customer has left and is no longer paying the subscription fee. On the other hand, the covert indirect churn effect arises from potential customers who never join the service due to a diminished user base (Proposition 1). This effect is referred to as 'covert' as it is not readily apparent to the firm - it never registers in the books, leaving the firm unaware of the lost potential customers.

Table 4: Loss of customer equity due to churn*

I	II Focal scenario	III New churn, keeping focal users' potential	IV Loss due to an increase in churn	V Focal scenario	VI New user potential, keeping focal churn	VII Loss due to decrease in users' potential
Churn	0.10	0.11		0.10	0.10	
Users Potential	668	668		668	635	
CLV	$50	$47.6		$50	$50	
Customer Equity	$3,937	$3,692	$245	$3,937	$3,742	$195
Percent of Total Loss			56%			44%

* Source: Simulation ($p = 0.001, q = 0.3, m = 1{,}000, g = \$10, i = 10\%, CAC = 0$)

We propose that this **covert indirect churn effect** could be as substantial as the cash flow loss from churning customers. We demonstrate this via Table 4: Consider columns II and V that depict a focal scenario of a 10% churn, that together with the rest of the parameters ($p = 0.001, q = 0.3, g = \$10, i = 10\%, CAC = 0, \mathrm{m} = 1{,}000$) yields a users' potential ($\overline{m}$) of 668 individuals. Using Equation 9 with a limited horizon (see Equation 27 in Appendix A), Customer Equity is $3,937. We limit the time horizon to 20 periods to make the case more realistic. We compare this focal scenario to two synthetic control scenarios (Columns III and VI) that answer the following: What would happen if we increased churn to 11%, but keep the user potential at the focal scenario level of 668? This will yield the loss due to increased churn only, net of the decline in user potential, thus reflecting the overt direct churn effect. Likewise, what would happen if we kept the focal level of churn yet decreased the user potential to the level commensurate with a churn of 11% ($\overline{m} = 635$)? The loss is due to a decrease in user potential net of the increase in churn, thus reflecting the covert indirect churn effect. Table 4 depicts one such scenario in which the loss because of churn on CLV is 56% of the total loss, while the decrease in user potential contributes to the rest – 44%.

Our simulation analysis suggests that the above case is not isolated. In a sizeable number of cases, the covert indirect churn was responsible for a substantial portion of the monetary loss from customer churn. This phenomenon can be affected by multiple factors, including the time horizon. A comprehensive examination requires analyses beyond this article's scope, yet we believe it is an essential subject with notable practical and theoretical implications.

Dynamic churn

Consistent with much of the modeling literature in this area, our basic approach assumed a stable churn rate over time. In practice, it may vary in specific situations. Dynamic churn has to be modeled carefully. If the change in churn affects all cohorts in the user base equally, that is, they all have the same churn at each period *t*, then Equation 2 still holds with $\delta(t)$ replacing δ. However, if each cohort's churn differs from other cohorts, then Equation 2 should be replaced with the following integral equation, which cannot be reduced to a differential equation:

$$(11)\ x(t) = \int_0^t I(s)e^{-\delta(s)(t-s)}ds$$

where $I(s) = (p + qx(s)/m)(m - x(s))$.

To see this more clearly, consider a firm with a stock of machines such as printers that it rents. These machines decay at the date of $\delta(t)$ for each batch that was produced at time period *t*. This decay rate is the analogy of churn in our setting. If the firm now decides to replace the stainless-steel ball-bearing with plastic ones, this will affect the decay of the current batch, but none of the previous batches, as the latter still use the steel bearing. Thus, each batch (cohort) decays at its own rate; consequently, Equation 11 is appropriate (Muller and Peles 1990). There are good reasons to believe this will be the case in XaaS firms too where cross-cohort heterogeneity will be reflected in different churn rates for different cohorts.

Net Dollar Retention

One of the interesting developments in the context of retention/churn is the move of firms to report Net Dollar Retention (NDR) instead or in addition to the measure of customer retention. NDR is based on the ARR curve and represents the rate of change of the amount of revenue from recurring customers in a period. It will include the effect on the revenue of current customers' downgrading (e.g., choosing a cheaper subscription plan), upgrading (buying more, for example, due to cross-selling or upselling), and the loss due to customer churn. It can be measured as

$$\text{Net Dollar Retention} = \frac{\text{starting ARR} + \text{revenue uprgading} - \text{revenue downgrading} - \text{loss due to churned customers}}{\text{starting ARR}}$$

In the XaaS growth framework context, NDR measurement represents a move from measuring retention based on the user curve (customer retention) to retention based on the money curve (NDR). The practice business literature illustrates NDR's emerging pivotal role for XaaS. NDR is described as the "one metric to rule them all," taking center stage as the "qualifying metric for determining the health of a SaaS business" (Tsang 2022). Firms are expected to report this measure to get funding, typically hoping to reach benchmarks above 100% (Heymann 2023). Practically, various SaaS firms have stopped writing customer churn rates in their financial reports, disclosing (if they do) only NDR.

The move to NDR symbolizes a significant development in marketing thinking. Customer retention has been recognized as a critical customer-related metric and the basis of numerous research studies (Ascarza et al. 2018). A fundamental change in its use in practice requires new thinking: While customer retention is still a part of NDR, the more recent metric demonstrates that customer development (cross-selling, upselling, etc.) takes a front seat in customer-related measurement for growth. This change opens research opportunities to compare the measures and analyze differential efficacy. Generally, it indicates an industry move from the more straightforward user curve measurement to the more holistic money curve and the need to take a holistic view of XaaS growth.

Reporting XaaS growth metrics

Of the four XaaS firms we reported in Table 2, namely, Peloton, Roku, SiriusXM and Spotify, all reported the number of users (under various definitions such as subscribers, active accounts, or monthly active users), yet only two reported the churn rate. This is quite surprising as this is a key figure indicating a subscription-based firm's operational and marketing health. Indeed, academics have developed ways to figure out the fundamental customer metrics from traditional financial reporting to enable valuation (McCarthy, Fader, and Hardie 2017).

Moreover, academics across disciplines argue that without informative customer measures, current financial disclosure rules allow would-be public companies to shape a rosy narrative about their prospects and disguise information that investors should know (Damodaran, McCarthy, and Cohen 2022). Similar sentiments of the need to report customer-based measures to conduct proper valuation come from consulting firms (Markey 2020) and executives (Brennan 2020). If the number of products sold in previous times may have been sufficient to value growth, the dominance of XaaS requires more compound measures. Like others, we believe it is time for regulators to adapt.

Advertising, pricing and competition

Advertising and pricing have been incorporated successfully into the diffusion of innovation framework however these efforts generally focused on first purchase scenarios (see Bass, Jain, and Krishnan 2000; Cosguner and Seetharaman 2022). These marketing mix variables were modeled to affect the growth parameters or the market potential and dynamic optimal policies were identified using the extended Bass model as the basic framework (Cosguner and Seetharaman 2022). These extended models and corresponding optimal policies could be replicated for the XaaS framework as well. Beyond the contribution to improved fit and prediction (Mesak, Scott, and Bari 2022) various first purchase marketing mix growth insights should be examined for the case of XaaS. For example,findings on customer purchase behviour for subscriptions (Iyengar, Park, and Yu 2022) and service pricing optimization (Wang, Dada, and Sahin 2019) can be used as a base to the thinking on how pricing will change in the growth of XaaS. Particularly the effects of churn on the optimal path of advertising and pricing offers further managerially relevant questions: For example, should an increase in churn increase or decrease optimal advertising levels?

The XaaS competitive framework is a more complex phenomenon as churning customers need to be divided into two: The customers who are churning to the competition, and those who are leaving the category altogether. Moreover, for any marketing mix variable, it is necessary to assess whether changes in advertising or pricing affects acquisition of new customers or the retention of current ones. Competitive diffusion models have offered a number ofways in brands can compete for the same market potential (see Libai, Muller and Peres 2009b) and various options can be used for such modeling for the growth of XaaS, depending of course on the assumptions on the narure of churn (Libai, Muller and Preres 2009).

It has to be noted however, that acquiring new customers via any subsidy or seeding campaign only serves to accelerate the acquisition of these potential customers, since if the market potential was defined correctly, these customers would be otherwise acquired sometime in the future and thus it is not their entire CLV that should be added as a benefit of such action, but just the benefit of having their CLV earlier (Libai, Muller and Peres 2013).

Conclusion

We believe that the transition to XaaS dominant markets is a challenge but simultaneously offers a rich spectrum of opportunities. The above exploratory propositions and demonstrations offer a comprehensive foundation to create a more holistic view of XaaS growth and hopefully guide the way for careful, and empirically supported analyses in subsequent research. Combining a product life cycle approach with the customer life cycle analysis will enable researchers to contribute to a fast-changing environment that continues to re-invent business practices and success measures.

Appendix A

This appendix proves analytically Propositions 1, 2, 5, and 6. For the sake of completeness, the appendix is self-contained, that is, it contains some repetition from the text. The model is a more straightforward version of Libai, Muller and Peres 2009 (henceforth LMP), without the term $(1-\delta)$ in the contagion coefficient. The model is given by:

$$(1)\ \frac{dx}{dt} = \left(p + \frac{qx}{m}\right)(m-x) - \delta x$$

LMP showed that this model is equivalent to the Bass model with the following new parameters (these parameters are now converted to the simpler model), that is, the solution of Equation1 is given by Equation 2:

$$(2)\ x(t) = \bar{m} \cdot F(t) = \bar{m} \cdot \frac{1 - e^{-(\bar{p}+\bar{q})t}}{1 + \left(\frac{\bar{q}}{\bar{p}}\right) \cdot e^{-(\bar{p}+\bar{q})t}} = \bar{m} \cdot \frac{1 - e^{-\Delta t}}{1 + \frac{\Delta+\beta}{\Delta-\beta} \cdot e^{-\Delta t}}$$

Where,

$$(3)\ \bar{p} = (\Delta - \beta)/2$$

$$(4)\ \bar{q} = (\Delta + \beta)/2$$

$$(5)\ \bar{m} = m(\Delta + \beta)/(2q)$$

$$(6)\ \beta = q - p - \delta$$

$$(7)\ \Delta = \sqrt{\beta^2 + 4qp}$$

Proposition 1: When churn (δ) increases, user potential ($\bar{m}$) declines, that is $\frac{\partial \bar{m}}{\partial \delta} \leq 0$.

Proof: First note that given Equation 6, it follows that $\frac{\partial \bar{m}}{\partial \delta} = -\frac{\partial \bar{m}}{\partial \beta}$. Next, it's straightforward to show that:

$$(8)\ \frac{\partial \Delta}{\partial \beta} = \frac{\beta}{\Delta}$$

Using Equations 5 and 9 yields the following:

$$(9)\ \frac{\partial \bar{m}}{\partial \delta} = -\frac{\partial \bar{m}}{\partial \beta} = -\frac{m}{2q} \cdot \left(1 + \frac{\beta}{\Delta}\right) \leq 0$$

Note that we will shortly constrain β to be nonnegative (for the peak time T^* to be nonnegative), yet here we need a weaker condition, $\bar{q} \geq 0$.

Proposition 2: The peak in the number of new adopters is ***later*** than the peak in the number of new users.

Proof: Recall that the relation between the number of new adopters to the number of new users is given by:

(10) $da/dt = dx/dt + \delta x$

Differentiate Equation 10 to verify that when $d^2x/dt^2 = 0$, $d^2a/dt^2 = \delta dx/dt > 0$.

Proposition 5: With an increase in churn, the relative size of the early market declines, while the relative size of main market increases.

Proof: We use the Appel and Muller (2021) and Mahajan, Muller and Srivastava (1990) frameworks and define the innovators and early adopters as early market while the majority (early and late) as main market.

The critical points, that is inflection points T_1 and T_2 and peak-time T^* are given by (see Mahajan Muller and Srivastava 1990, and Figure 6 in the main text):

$$(11)\ T_1 = +\frac{1}{\bar{p}+\bar{q}}\ln\left(\frac{\bar{q}}{\bar{p}\cdot(2+\sqrt{3})}\right) = T^* - \frac{1}{\Delta}\cdot\ln(2+\sqrt{3})$$

$$(12)\ T_2 = +\frac{1}{\bar{p}+\bar{q}}\ln\left(\frac{\bar{q}\cdot(2+\sqrt{3})}{\bar{p}}\right) = T^* + \frac{1}{\Delta}\cdot\ln(2+\sqrt{3})$$

$$(13)\ T^* = +\frac{\ln\left(\frac{\bar{q}}{\bar{p}}\right)}{(\bar{p}+\bar{q})} = \frac{1}{\Delta}\cdot\ln\left(\frac{\Delta+\beta}{\Delta-\beta}\right)$$

For T^* to be nonnegative, we need the log in the RHS of Equation 13 to be nonnegative and thus we need $\Delta + \beta \geq \Delta - \beta$ which implies that $\beta \geq 0$. For p to be nonnegative we need $\Delta \geq \beta$, which obviously holds given Equation 6. As this appendix investigates the effects of churn δ on the adopters' categories and the timing and size of peak sales, for the rest of the analysis we assume that $T^* \geq 0$, that is, $\beta \geq 0$.

Let *M* be the size of the early majority. From MMS we can easily show that *M* is given by:

$$(14)\ M = \frac{1}{\sqrt{12}}\cdot\frac{2\Delta}{\Delta+\beta}$$

As the sizes of the early and late majority are equal, the main market is equal to $2 \cdot M$, and thus showing that the main market increases with churn, is equivalent to showing that *M* increases with churn, and thus:

$$(15)\ \frac{\partial M}{\partial \delta} = -\frac{\partial M}{\partial \beta} = -\frac{2}{\sqrt{12}}\cdot\frac{(\Delta+\beta)\cdot\frac{\partial \Delta}{\partial \beta} - \Delta\cdot(\frac{\partial \Delta}{\partial \beta}+1)}{(\Delta+\beta)^2} = -\frac{2}{\sqrt{12}}\cdot\frac{\beta\cdot\frac{\partial \Delta}{\partial \beta} - \Delta}{(\Delta+\beta)^2}$$

Using Equation 8 we have:

$$(16)\ \frac{\partial M}{\partial \delta} = -\frac{2}{\sqrt{12}} \cdot \frac{\beta^2 - \Delta^2}{\Delta(\Delta+\beta)^2} = +\frac{2}{\sqrt{12}} \cdot \frac{\Delta - \beta}{\Delta(\Delta+\beta)} \geq 0$$

With strict inequality when $\Delta > \beta$, that is, when both *p* and *q* are positive.

We can also show that when δ increases, $T_2 - T^*$ and $T^* - T_1$ increase:

$$(17)\ T_2 - T^* = T^* - T_1 = \frac{1}{\Delta} \cdot \ln(2+\sqrt{3})$$

$$(18)\ \partial(T_2 - T^*)/\partial\delta = \partial(T^* - T_1)/\partial\delta = \ln(2+\sqrt{3}) \cdot \frac{\beta}{\Delta^3} \geq 0$$

Next, we show that the early market declines in size when δ increases. From MMS the early market category size *E* is given by:

$$(19)\ E = \frac{1}{2} \cdot \left(1 - \frac{\Delta - \beta}{\Delta + \beta}\right) - \frac{1}{12} \cdot \left(1 + \frac{\Delta - \beta}{\Delta + \beta}\right) = \frac{5}{12} - \frac{5}{12} \cdot \frac{\Delta - \beta}{\Delta + \beta}$$

$$(20)\ \frac{\partial E}{\partial \delta} = -\frac{\partial E}{\partial \beta} = \frac{5}{12} \cdot \frac{\left(\frac{\partial \Delta}{\partial \beta} - 1\right)(\Delta + \beta) - \left(\frac{\partial \Delta}{\partial \beta} + 1\right)(\Delta - \beta)}{(\Delta+\beta)^2} = \frac{10}{12} \cdot \frac{\beta \frac{\partial \Delta}{\partial \beta} - \Delta}{(\Delta+\beta)^2}$$

Using equation 8 we have:

$$(21)\ \frac{\partial E}{\partial \delta} = \frac{10}{12} \cdot \frac{\beta^2 - \Delta^2}{\Delta \cdot (\Delta+\beta)^2} = -\frac{10}{12} \cdot \frac{\Delta - \beta}{\Delta \cdot (\Delta+\beta)} \leq 0$$

Proposition 6: Customer Equity of a XaaS firm is given by either the CLV method (Equation 22) or the ARR method (Equation 23). In other words, these two measures are equivalent. With a finite horizon, the CLV methods yields a higher value that more accurately reflects the true customer equity.

$$(22)\ \pi_{CLV} = \int_0^\infty (CLV - CAC) \cdot \frac{da}{dt} \cdot e^{-it} dt$$

$$(23)\ \pi_{ARR} = \int_0^\infty \left(g \cdot x(t) - CAC \cdot \frac{da}{dt}\right) \cdot e^{-it} dt$$

Proof: With no acquisition costs, customer equity is given by:

$$(24)\ \pi = \int_0^\infty CLV \cdot \frac{da}{dt} \cdot e^{-it} dt = CLV \cdot \int_0^\infty \left\{\frac{dx}{dt} + \ \delta x(t)\right\} \cdot e^{-it} dt$$
$$= \frac{g}{(i+\delta)} \cdot \int_0^\infty \left\{\frac{dx}{dt} + \ \delta x(t)\right\} \cdot e^{-it} dt$$

We wish to show that π can also be written as:

$$(25)\ \pi = \int_0^\infty g \cdot x(t) \cdot e^{-it} dt$$

The way to show it is to take the first part of Equation 14, and integrate by parts:

$$\int_0^\infty \left\{\frac{dx}{dt}\right\} e^{-it}dt = \lim_{t\to\infty} x(t)e^{-it} - \lim_{t\to 0} x(t)e^{-it} + i\int_0^\infty x(t)e^{-it}dt = \int_0^\infty i\cdot x(t)e^{-it}dt$$

Where the last equality follows the fact that $x(\infty)$ is finite, and $x(0) = 0$. Thus:

$$(26)\ \pi = \frac{g}{(i+\delta)}\cdot\int_0^\infty \left\{\frac{dx}{dt} + \ \delta x(t)\right\}\cdot e^{-it}dt$$
$$= \frac{g}{(i+\delta)}\cdot\int_0^\infty \{ix(t) + \ \delta x(t)\}\cdot e^{-it}dt = g\cdot\int_0^\infty x(t)\cdot e^{-it}dt$$

Adding customer acquisition costs (*CAC*) simply subtracts the same term $\int_0^\infty CAC\cdot\frac{da}{dt}\cdot e^{-it}dt$ from both equations.

For the finite horizon case, denote by $\pi_{CLV,T}$ the customer equity up to time horizon *T*, according to the CLV approach, and similarly $\pi_{ARR,T}$ according to the ARR approach. Note that we abstract from the costs of acquiring these users as the exact same costs term is subtracted from both cases, namely: $\int_0^T CAC\cdot\frac{da}{dt}\cdot e^{-it}dt$.

$$(27)\ \pi_{CLV,T} = \int_0^T CLV\cdot\frac{da}{dt}\cdot e^{-it}dt$$

$$(28)\ \pi_{ARR,T} = \int_0^T g\cdot x(t)\cdot e^{-it}dt$$

We now employ the same integration by parts of the CLV approach that yields the following:

$$\int_0^T \left\{\frac{dx}{dt}\right\} e^{-it}dt = x(T)e^{-iT} - \lim_{t\to 0} x(t)e^{-it} + i\int_0^\infty x(t)e^{-it}dt$$
$$= x(T)e^{-iT} + \int_0^\infty i\cdot x(t)e^{-it}dt$$

Thus,

$$(29)\ \pi_{CLV,T} = \frac{g}{(i+\delta)}\cdot\int_0^T \left\{\frac{dx}{dt} + \ \delta x(t)\right\}\cdot e^{-it}dt$$
$$= \frac{gx(T)e^{-iT}}{(i+\delta)} + \frac{g}{(i+\delta)}\cdot\int_0^T \{ix(t) + \ \delta x(t)\}\cdot e^{-it}dt = \frac{gx(T)e^{-iT}}{(i+\delta)}$$
$$+ g\int_0^T x(t)\cdot e^{-it}dt = CLV\cdot x(T)\cdot e^{-iT} + \int_0^T g\cdot x(t)\cdot e^{-it}dt$$

It follows that,

$$(30)\ \pi_{CLV,T} = CLV\cdot x(T)\cdot e^{-iT} + \pi_{ARR,T}$$

And thus,

(31) $\pi_{CLV,T} > \pi_{ARR,T}$

As both measures undervalue the true customer equity (the one with infinite horizon), it follows that for the finite horizon, the CLV method is more accurate.

Reference

Agility (2022), "22 strategies for customer lifecycle marketing," available at https://agilitycms.com/resources/posts/22-strategies-for-customer-lifecycle-marketing

Appel, Gil and Eitan Muller (2021), "Adoption patterns over time: A replication," *Marketing Letters*, (32), 32(4), 499-511.

Ascarza, Eva, Scott A. Neslin, Oded Netzer, Zachery Anderson, Peter S. Fader, Sunil Gupta, Bruce Hardie, Aurélie Lemmens, Barak Libai, David Neal, and Foster Provost (2018), "In pursuit of enhanced customer retention management: Review, key issues, and future directions," *Customer Needs and Solutions,* 5(1-2), 65-81.

Bhattacharya, Shantanu, and Lipika Bhattacharya (2021), *XaaS: Everything-as-a-Service: The Lean and Agile Approach to Business*, World Scientific.

Bass, Frank M., Dipak Jain, and Trichy Krishnan (2000) "Modeling the marketing-mix influence in new-product diffusion," in Vijay Mahajan, Eitan Muller and Yoram Wind (eds.), *New-Product Diffusion Models*, 99-122.

Ben Rhouma, Tarek and Georges Zaccour (2018), "Optimal marketing strategies for the acquisition and retention of service subscribers," *Management Science*, 64(6), 2609-2627.

Bertini, Marco, and Oded Koenigsberg (2020), *The Ends Game: How Smart Companies Stop Selling Products and Start Delivering Value*, MIT Press.

Brennan, Jack (2020), "Over time, the market will demand this information," *Harvard Business Review*, 98(1), 56-57.

Chen, Tony, Ken Fenyo, Sylvia Yang, and Jessica Zhang (2018), "Thinking inside the subscription box: New research on e-commerce consumers," *McKinsey*, February 9, available at https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/thinking-inside-the-subscription-box-new-research-on-ecommerce-consumers

Chandrasekaran, Deepa and Gerard J. Tellis (2018), "A summary and review of new product diffusion models and key findings," in *Handbook of Research on New Product Development*, Edward Elgar Publishing.

Cosguner, Koray, and P. B. Seetharaman (2022), "Dynamic pricing for new products using a utility-based generalization of the bass diffusion model," *Management Science*, 68(3), 1904-1922.

Damodaran, Aswath, Daniel M. McCarthy, and Maxime C. Cohen (2022), "IPO disclosures are ripe for reform," *MIT Sloan Management Review*, 63(4), 55-61.

Du, Rex Yuxing, Oded Netzer, David A. Schweidel, and Debanjan Mitra (2021), "Capturing marketing information to fuel growth," *Journal of Marketing*, 85(1), 163-183.

Fader, Peter S. and Bruce GS Hardie (2015), "Simple probability models for computing CLV and CE," in V. Kumar and Denish Shah (eds.), *Handbook of Research on Customer Equity in Marketing*, Edward Elgar Publishing.

Favoretto, Camila, Glauco HS Mendes, Maicon G. Oliveira, Paulo A. Cauchick-Miguel, and Wim Coreynen (2022), "From servitization to digital servitization: How digitalization transforms companies' transition towards services," *Industrial Marketing Management*, 102, 104-121.

Fischer, Marc, Peter SH Leeflang, and Peter C. Verhoef (2010), "Drivers of peak sales for pharmaceutical brands," *Quantitative Marketing and Economics*, 8(4), 429-460.

Foutz, Natasha Zhang (2017), "Entertainment marketing," *Foundations and Trends in Marketing*, 10(4), 215-333.

Gelper, Sarah, Renana Peres, and Jehoshua Eliashberg (2018), "Talk bursts: The role of spikes in prerelease word-of-mouth dynamics," *Journal of Marketing Research*, 55(6), 801-817.

Georgiadis, Candice (2023), "What challenges do startups face and how can you overcome them?," *Forbes*, January, available at https://www.forbes.com/sites/theyec/2023/01/13/what-challenges-do-startups-face-and-how-can-you-overcome-them/?sh=5ec3cc92772c

Goldenberg, Jacob, Barak Libai, and Eitan Muller (2002), "Riding the saddle: How cross-market communications can create a major slump in sales," *Journal of Marketing*, 66(2), 1-16.

Goldenberg, Jacob, Barak Libai, and Eitan Muller (2010), "The chilling effects of network externalities," *International Journal of Research in Marketing*, 27(1), 4-15.

Golder, Peter N., and Gerard J. Tellis (2004), "Growing, growing, gone: Cascades, diffusion, and turning points in the product life cycle," *Marketing Science*, 23(2), 207-218.

Gupta, Sunil, Donald R. Lehmann, and Jennifer Ames Stuart (2004), "Valuing customers," *Journal of Marketing Research*, 41(1), 7-18.

Harrington, Chase (2022), "Growth vs. profitability: How businesses can survive a market shift," *Forbes*, December, available at https://www.forbes.com/sites/forbesbusinesscouncil/2022/12/21/growth-vs-profitability-how-businesses-can-survive-a-market-shift/?sh=14fe4b23f8ec

Haenlein, Michael, Barak Libai, and Eitan Muller (2023), "Satiation and cross promotion: Selling and swapping users in mobile games," *International Journal of Research in Marketing*, 40(2), 342-361.

Heim, Anna (2022), "Investors have flipped their weighting of growth versus profitability," *TechCrunch*, June, available at https://techcrunch.com/2022/06/02/investors-have-flipped-their-weighting-of-growth-versus-profitability/

Heymann, Paris (2023), "Acquisition, retention, expansion: Why SaaS founders must understand GDR and NDR," *TechCrunch*, May, available at https://techcrunch.com/2023/05/04/acquisition-retention-expansion-why-saas-founders-must-understand-gdr-and-ndr/

Hogan, John E., Katherine N. Lemon, and Barak Libai (2003), "What is the true value of a lost customer?" *Journal of Service Research*, 5(3), 196-208.

Iyengar, Raghuram, Young-Hoon Park, and Qi Yu (2022), "The impact of subscription programs on customer purchases," *Journal of Marketing Research*, 59(6), 1101-1119.

Kotler, Philip, Kevin Keller, and Alexander Chernev (2021), *Marketing Management*, 16 ed., Pearson.

Kowalkowski, Christian, Heiko Gebauer, Bart Kamp, and Glenn Parry (2017), "Servitization and deservitization: Overview, concepts, and definitions," *Industrial Marketing Management*, 60, 4-10.

Kowalkowski, Christian, and Wolfgang Ulaga (2024), "Subscription offers in business-to-business markets: Conceptualization, taxonomy, and framework for growth," *Industrial Marketing Management*,117, 440-456.

Kumar, V. and Denish Shah (2008), "Expanding the role of marketing: from customer equity to market capitalization," *Journal of Marketing*, 73(6), 119-136.

Landsman, Vardit, and Irit Nitzan (2020), "Cross-decision social effects in product adoption and defection decisions," *International Journal of Research in Marketing*, 37(2), 213-235.

Lehmann, Donald R., and Mercedes Esteban-Bravo (2006), "When giving some away makes sense to jump-start the diffusion process," *Marketing Letters*, 17(4), 243-254.

Libai, Barak, Eitan Muller, and Renana Peres (2009), "The diffusion of services," *Journal of Marketing Research*, 46(2), 163-175.

Libai, Barak, Eitan Muller, and Renana Peres (2009b), "The role of within-brand and cross-brand communications in competitive growth." *Journal of Marketing,* 73(3), 19-34.

Libai, Barak, Eitan Muller, and Renana Peres (2013), "Decomposing the value of word-of-mouth seeding programs: Acceleration versus expansion," *Journal of Marketing Research*, 50(2), 161-176.

Liberto, Daniel (2022), "Recurring revenue: Types and considerations," Investopedia, available at: https://www.investopedia.com/terms/r/recurringrevenue.asp

Mahajan, Vijay, Eitan Muller, and Rajendra K. Srivastava (1990), "Determination of adopter categories by using innovation diffusion models," *Journal of Marketing Research*, 27(1), 37-50.

Mankins, Michael (2017), "Stop focusing on profitability and go for growth," *Harvard Business Review*, May, available at https://hbr.org/2017/05/stop-focusing-on-profitability-and-go-for-growth

Markey, Rob (2020), "Are you undervaluing your customers?" *Harvard Business Review*, 98(1), 42-50.

Mesak, Hani I., C. Patrick Scott, and Abdullahel Bari (2022), "On the diffusion of subscription-based services: The roles of price, advertising, and customers' defection," *IEEE Transactions on Engineering Management*, 71, 2212-2225

McCarthy, Daniel M., Peter S. Fader, and Bruce GS Hardie (2017), "Valuing subscription-based businesses using publicly disclosed customer data," *Journal of Marketing*, 81(1), 17-35.

Meade, Nigel, and Towhidul Islam (2006), "Modelling and forecasting the diffusion of innovation–A 25-year review," *International Journal of Forecasting,* 22(3), 519-545.

Miller, Grant, (2018), "After 20 years of Salesforce, what Marc Benioff got right and wrong about the cloud," Tech Crunch, available at https://techcrunch.com/2018/06/17/after-twenty-years-of-salesforce-what-marc-benioff-got-right-and-wrong-about-the-cloud/

Moe, Wendy W., and Peter S. Fader (2002), "Using advance purchase orders to forecast new product sales," *Marketing Science*, 21(3), 347-364.

Moldovan, Sarit, Eitan Muller, Yossi Richter, and Elad Yom-Tov (2017), "Opinion leadership in small groups," *International Journal of Research in Marketing*, 34(2), 536-552.

Muller, Eitan, and Yoram C. Peles (1990), "Optimal dynamic durability," *Journal of Economic Dynamics and Control*, 14(3), 709-719.

Muller, Eitan and Guy Yogev (2006), "When does the majority become a majority? Empirical analysis of the time at which main market adopters purchase the bulk of our sales," *Technological Forecasting and Social Change*, 73(9), 1107-1120.

Nitzan, Irit, and Barak Libai (2011), "Social effects on customer retention," *Journal of Marketing*, 75(6), 24-38.

Ofek, Elie, Barak Libai and Eitan Muller (2022), "On CUE: The quest for optimal customer unit economics," *Harvard Business School Industry and Background Note* (9-523-050).

Paddle (2023), *What is annual recurring revenue (ARR) and how to calculate it*, available at https://www.paddle.com/resources/annual-recurring-revenue

Palmer, Douglas (2021), "The top five metrics driving SaaS company valuations," *Forbes*, September 1, Available at https://www.forbes.com/sites/forbesfinancecouncil/2021/09/01/the-top-five-metrics-driving-saas-company-valuations/?sh=626e284c770b

Parative (2024), *ARR Growth Rate*, available at https://www.parative.com/glossary-term/arr-growth-rate#:~:text=ARR%20Growth%20Rate%20is%20an,subscriptions%20and%20other%20recurring%20sources.

Peres, Renana, Eitan Muller, and Vijay Mahajan (2010), "Innovation diffusion and new product growth models: A critical review and research directions," *International Journal of Research in Marketing*, 27(2), 91-106.

Rogers, Everett M. (2003), *Diffusion of Innovations*, Free Press.

Rust, Roland T., Katherine N. Lemon, and Valarie A. Zeithaml (2004), "Return on marketing: Using customer equity to focus marketing strategy," *Journal of Marketing*, 68(1), 109-127.

Rust, Roland T., and Ming-Hui Huang (2014), "The service revolution and the transformation of marketing science," *Marketing Science*, 33(2), 206-221.

Saasquatch (2023), "What is customer lifecycle marketing?" available at https://www.saasquatch.com/blog/what-is-customer-lifecycle-marketing

Sacks, David and Ethan Ruby (2021), "The SaaS metrics that matter," October, available at https://sacks.substack.com/p/the-saas-metrics-that-matter

Salesforce (2023), "How to calculate recurring revenue," available at https://www.salesforce.com/resources/articles/how-to-calculate-recurring-revenue/

Schulze, Christian, Bernd Skiera, and Thorsten Wiesel (2012), "Linking customer and financial metrics to shareholder value: The leverage effect in customer-based valuation," *Journal of Marketing*, 76(2), 17-32.

Skiera, Bernd, and Christian Schulze (2014), "Customer-based valuation: similarities and differences to traditional discounted cash flow models," in *Handbook of Service Marketing Research*, Roland Rust and Min-Hui Huang (eds.), Edward Elgar Publishing, 123-134.

Skok, David (2017), "SaaS Metrics 2.0 – A guide to measuring and improving what matters," *For Entrepreneurs*, available at https://www.forentrepreneurs.com/saas-metrics-2/

Tzuo, Tien, and Gabe Weisert (2018), *Subscribed: Why the subscription model will be your company's future-and what to do about it*, Penguin.

Tsang, You Mon (2022), "Why NRR (Net Revenue Retention) is the one metric to rule them all for SaaS," *Forbes*, April, available at https://www.forbes.com/sites/forbesbusinesscouncil/2022/04/15/why-nrr-net-revenue-retention-is-the-one-metric-to-rule-them-all-for-saas/?sh=2ad7f5a16873

Van den Bulte, Christophe, and Yogesh V. Joshi (2007), "New product diffusion with influentials and imitators," *Marketing Science*, 26(3), 400-421.

Vargo, Stephen L., and Robert F. Lusch (2004), "Evolving to a new dominant logic for marketing," *Journal of Marketing,* 68(1), 1-17.

Villanueva, Julian, and Dominique M. Hanssens (2008), "Customer equity: Measurement, management and research opportunities," *Foundations and Trends in Marketing*, 1(1), 1-95.

Wang, Ruxian, Maqbool Dada, and Ozge Sahin (20190, "Pricing ancillary service subscriptions," *Management Science*, 65(10), 4712-4732.

Wilhelm, Alex (2023), "Tech investors' obsession over profit is already waning," *TechCrunch*, April, available at https://techcrunch.com/2023/04/17/tech-investors-obsession-profit-waning/

Wiesel, Thorsten, Bernd Skiera, and Julian Villanueva (2008), "Customer equity: An integral part of financial reporting," *Journal of Marketing*, 72(2), 1-14.

Yahoo Finance (2023),"Lemonade turns to synthetic agents to finance growth," June, available at https://finance.yahoo.com/news/lemonade-turns-synthetic-agents-finance-110000293.html

Zhang, Hao, and Yung Kyun Choi (2018), "Preannouncement messages: impetus for electronic word-of-mouth," *International Journal of Advertising*, 37(1), 54-70.

Web Appendix B

This web appendix specifies the details of the simulations that demonstrate Propositions 3, 4, and 6. We define the parameters of interest with diffusion parameters in the range $0.001 \leq p \leq 0.07$, and $0.2 \leq q \leq 0.8$, consistent with the ranges observed in the new product literature. We define the churn rate range of $0.05 \leq \delta \leq 0.5$. The four propositions we are testing here do not depend on the market potential m, thus for convenience we fix m at 1,000. We then calculate and report for each proposition the relevant outcome of interest.

Proposition 3: With an increase in churn, the peak in the number of new users decreases, while the time to peak increases in most cases. However, for early skewed growth, the time to peak might decrease.

Simulations: We first draw values of p in the range indicated above (we use increasing increments of 0.001, starting from $p = 0.001$). For each of these simulations of p we run simulations of q starting at 0.2 and increasing in increments 0.05 until a maximum of 0.8. For each of these nested simulations of combinations of p and q we increase from 0.05 in increasing increments of 0.01 until the maximum of 0.5. We exclude simulations with a negative T^*.

For all combinations of p and q, the time to the peak will at some point reverse and decrease with increasing churn. Given that we restrict our churn values to a maximum of 0.5, for large q we do not observe a reversal in simulations with a faster diffusion as the reversal will only take place with churn greater 0.5.

Within each combination of p and q we observe that the majority of cases of increasing churn lead to a later peak and a lower level of the peak. Thus, we calculate for each combination of p and q the proportion of cases in which increasing churn leads to an increase of the peak. We find that across all unique combinations of p and q the average proportion of cases in which the peak time increases with increasing churn is 88%.

For the remaining cases in which the proposition does not hold and we find that the time to the peak decreases with increasing churn, we identify two reasons:

1) For early skewed growth (large p and q), the time to the peak can decrease.
2) When the number of active users is very low, i.e., the curve becomes flat, the proposition does not hold, and we observe a decrease in time to peak.

Figure B1 shows the relation of p and the proportion of cases in which churn is increasing and Figure B2 shows the relation of q and the proportion of cases in which churn is increasing. Both Figures support that for early skewed growth the time to peak can decrease. The correlation between p and the proportion of cases of increasing churn is $\rho = 0.21$, $p < 0.01$ and the correlation between q and the proportion of cases of increasing churn is $\rho = 0.86$, $p < 0.01$.

Figure B1:

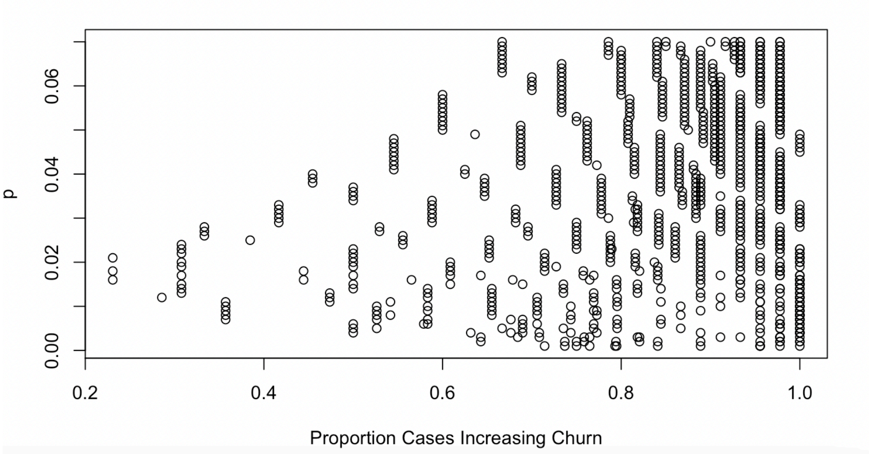
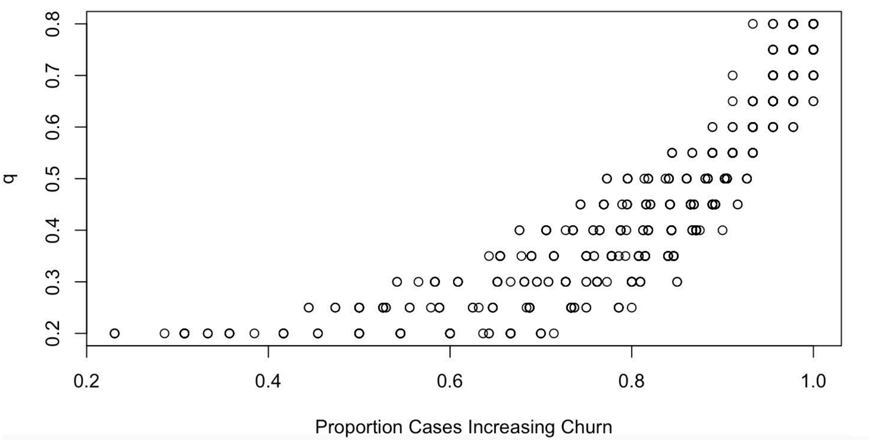
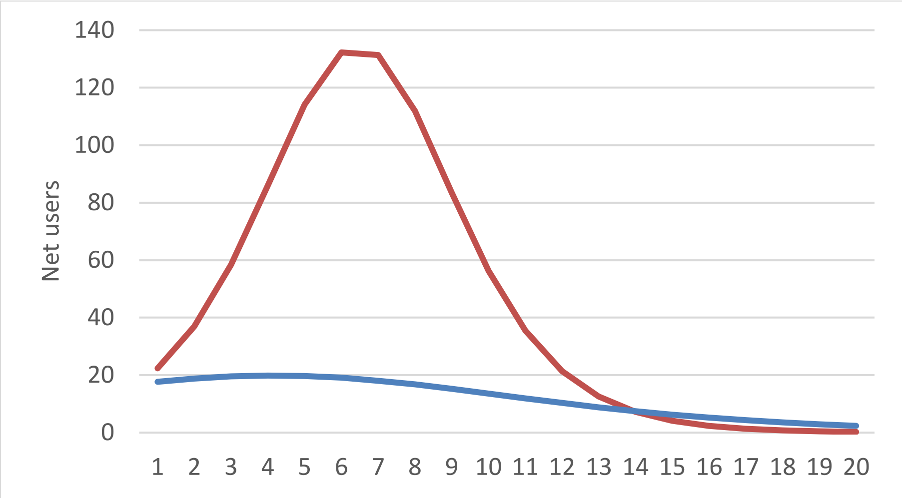


Figure B2:



Looking more specifically into cases for a decreasing peak that have a lower p value, we see that the value of churn is very large. This implies that the curves become very flat with a very small number of new users. Take for example the case in Figure B3 we plot dx/dt using a churn of 0.50, $p = 0.017$, and $q = 0.60$ (blue) and compare it to the case where churn is of 0.05, with the same p and q (red).

Figure B3: Net users, simulation $p = 0.017$, and $q = 0.60$, churn = 0.05 (red), 0.50 (blue)



Proposition 4: With an increase in the effect of buzzers, the time to peak in the number of users declines, and above a certain threshold the user curve is monotonically decreasing. The larger the effect of buzzers, the ***flatter*** is the initial decline of the user curve.

Simulations: We run 10,000 simulations with random draws of p and q in the ranges based on prior literature ($0.001 \leq p \leq 0.07$, and $0.2 \leq q \leq 0.8$). We fix churn at 0.05 and m at 100,000. For each combination of p and q we increase the number of buzzers in period 0 from 500 in increments of 500 to 50,000.

We find that the time the time to peak in the number of users declines for all simulations and that the larger the effect of buzzers in a monotonically decreasing user curve, the flatter becomes the initial decline of the user curve, which we measure by the decline in the first three periods after the decline.

Proposition 6: Faster customer acquisition causes the cashflow trough, that is the maximum negative cashflow, to become more negative.

Simulations: We run a simulation in which we draw first values of p (increasing in increments of 0.001, starting from 0.001). For each of these simulations of p we draw q starting at 0.2 and increasing in increments 0.05 until a maximum of 0.08. For each of these nested simulations of combinations of p and q we run 10 simulations of churn, starting at a churn value of 0.05 and increasing it in increments of 0.05 until the maximum of 0.5. We exclude simulations with a negative T^*.

Of the 8,372 simulations with a non-negative T^* we find that for all combinations of churn and p the maximum negative cashflow, becomes more negative with an increasing q. Our results thus show that faster customer acquisition causes the cashflow trough, which implies the maximum negative cashflow becomes more negative.