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

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Abstract

Broadly speaking, 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 a 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, require innovative frameworks that go beyond mere adoption metrics. In fact, XaaS metrics like ARR (Annual Recurring Revenue), Net Dollar Retention, and Unit Economics (customer lifetime value divided by customer acquisition costs) have become fundamental in evaluating and managing new ventures and products. The shift towards XaaS thinking, however, remains underrepresented in the methods marketing researchers use to model and understand growth.

Our objective is to introduce 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 delve into key metrics and paradigms in this domain, offering insights on the trajectory of these tiers and their interconnections. We also outline the ramifications of redirecting new product growth research towards the burgeoning 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 as early as 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). 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).

The current central role of XaaS framework presents a fundamental challenge for researchers and managers interested in the growth and profitability of new products. Historically, new product growth analyses were based on first-purchase models and have been primarily applied to durable goods. Since durables' monetization happens at adoption, the durable growth model could provide a good picture of the expected temporal profitability and could thus be helpful for prediction and planning. However, for a XaaS product, the adoption is just the start of a relationship and provides limited insights into profitability. This disparity raises a question of the relevance of classic work in the new product growth area for contemporary markets.

This issue is particularly essential since monetary growth questions are 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 *Unit Economics*, defined as CLV/CAC (Ofek, Libai and Muller 2022, Gupta, Lehmann, and Stuart 2004). However, managers and finance professionals such as CFO's and other stakeholders (including venture capital analysts, consultants, and investors) are often interested, and are expected to report, the period-by-period evolution of profitability over time (McCarthy, Fader and Hardie 2017). Period-by-period measures such as *Annual Recurring Revenue* (ARR), or its monthly equivalent MRR, have become fundamental analysis measures for XaaS firms, and the monetary measure of *Net Dollar Retention* (NDR) is reported in addition to or instead of the customer retention rate (Palmer 2021).

Building on the outlined evolution of business models and metrics applied to assess profitability and growth, we suggest that researchers and managers consider three growth curve types to analyze XaaS markets. The first is the ***adoption growth***, which indicates the number of new adopters. The required next step is to understand ***user growth***, representing the number of users over time, taking into account post-adoption churn. Indeed, 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 evaluated in the form of users over time rather than adopters. It is thus interesting to note while the shape and turning points of the adoption curve have been much studied in the academic literature (Golder and Tellis 2004; Goldenberg Libai and Muller 2002), we know little about the form of the user curve and what affects it.

The final growth of interest is ***monetary growth***. Monetary growth analysis can be based on the adoption curve and customer lifetime value assessment, or the user curve and period-by-period margin. In the latter case, there is an additional issue of whether to focus on recurring revenue as done in ARR analysis or to consider customer acquisition costs. Beyond the immediate contribution of the monetary curve to the practical management of XaaS valuation and growth, there is also an apparent theoretical motivation. The marketing function in the firm aims to build market-based assets that will enable it to accelerate, enhance and manage its cash flows (Srivastava, Shervani, and Fahey 1998). To study the role of marketing we should understand how XaaS firms generate the cashflows.

It follows, of course, that there is a sequence from the adoption to the users and then the monetary curve. For example, we consider the case of Buzzers, that is, individuals 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. Like buzzers, other marketing phenomena will affect the adoption, user and monetary curve and will create a chain of effects in the XaaS context.

In light of the above, our aim is to present an exploratory analysis of the growth of XaaS products across the three curves. To do so, we combine a *Product Life Cycle* view based on the diffusion of innovation thinking with a *Customer Life Cycle* view that focuses on what consumers do. We are helped by a XaaS growth model adapted from the service diffusion model of Libai, Muller, and Peres (2009) and use it to investigate the patterns of growth of the user and the monetary curves. 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 one first step in this direction.

The article proceeds as follows: In the next two sections, we present the framework and the model to describe XaaS growth. We then examine user growth in Section Four and the monetary growth of the XaaS firm in the following section. We conclude with a discussion that highlights the managerial implications of our work.

2. Customer life cycle and XaaS growth

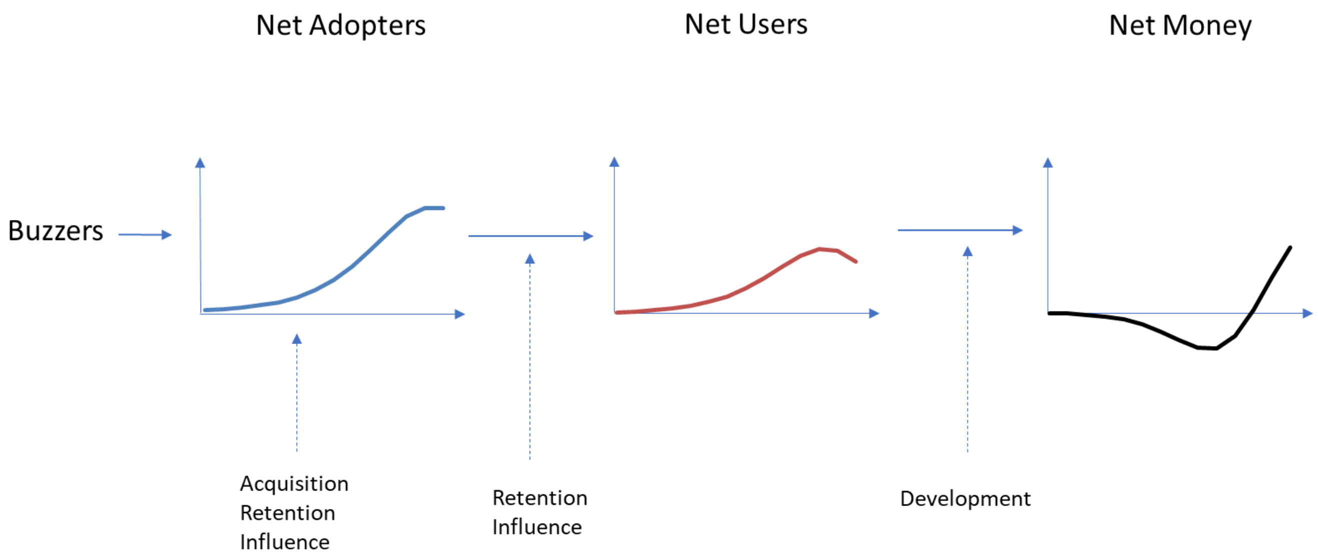
The Product Life Cycle (PLC) is a key framework for examining market growth and is an integral part of marketing textbooks (Kotler, Keller, and Chernev 2021). The theoretical base for the shape of the PLC has been primarily attributed to diffusion theory which describes how innovations spread in a market (Golder and Tellis 2004). The quantitative analysis of product growth has thus been 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). Since recognizing the shape and dynamics of growth are essential for the ability to predict, launch, value, and manage new products, these analyses are of key significance for marketers (Chandrasekaran and Tellis 2018). With a few exceptions, these were first-purchase models considering the first adoption over time. 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).

However, post-adoption customers often have a temporal recurring consumption relationship with the supplier. The customer relationship management literature has focused on how these 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 both 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[1]:

Figure 1: XaaS Value Chain



Looking at the left side of 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

[1] We shortly distinguish between adopters, users, and money and net adopters, net adopters, and net money.

also affect adoption: When people disadopt, the number of previous adopters that can influence new adopters goes down, which will affect the speed of adoption (Hogan, Lemon and Libai 2004).

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 when the product is launched, 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.

We distinguish between the user base, that is 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 it. But 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 thus function of the size of previous cohorts and the time elapsed since they have 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 decision of others (Landsman and Nitzan 2020; Moldovan et al. 2017). Thus, retention affects the user curve in two ways: first it affects the shape of the adoption curve, and then the transition from adoption to usage.

Lastly, converting users into revenues or profits is straightforward in the case where the average revenue per user (ARPU) remains the same over time. However, it is well documented, that ARPU is unlikely to remain constant: For example, in mobile games, it may significantly decline over time due to satiation (Haenlein, Libai and Muller 2023). In other industries, firms proactively increase cross-selling and upselling. That is, they engage in the ***development*** of the user base, and thus the temporal aspect of the user base is central to the revenue stream of the firm. In addition, usage captures heterogeneity among consumers, for example, the consumers' pattern of change of usage and their churn rate that affects the composition of the user base over time. The transition from the user curve to the monetary curve may thus not be straightforward.

3. Modeling XaaS growth

Towards a closer analysis of XaaS growth, consider the case of the media streamer *Roku* (www.roku.com): Consumers buy the streamer, and using their home network, stream TV shows and movies from various vendors such as Netflix, buy TV shows, and are exposed to ads. Thus, an average user begins with adopting the hardware, and then shifts to post-adoption behavior. If we take the latest available data, in 2022, Roku's revenues from adoption – that is, the hardware sales – were about \$415m, while post-adoption sales, mostly of advertising, amounted to \$2.7b. For every dollar Roku earns from adopting its hardware, it gets more than six times in revenues from its service (Roku 2022 Annual Report, p. 69). Here, the critical factor in the growth of users, as opposed to adopters, is churn. Table 1 depicts the number of users of Roku – the streaming service, and the number of new adopters. To explain Table 1, we need the following definitions that is essential to the XaaS growth model[2]:

- **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.

[2] 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.

- **Net Users** – dx/dt – change in the number of users over time.

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

Table 1: Users and adopters of Roku streaming service, world-wide, 2022*

	Roku active users at the end of the year (in thousands)	
2022	x_{t+1}	70,000
2021	x_t	60,100
Net addition (net users)	$x_{t+1} - x_t$	9,900
Churn	δx_t ($\delta = 20\%$[3])	14,000
Actual number of new adopters in 2022 (net adopters)	$x_{t+1} - x_t + \delta x_t$	23,900

* Source: Roku 2022 annual report

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

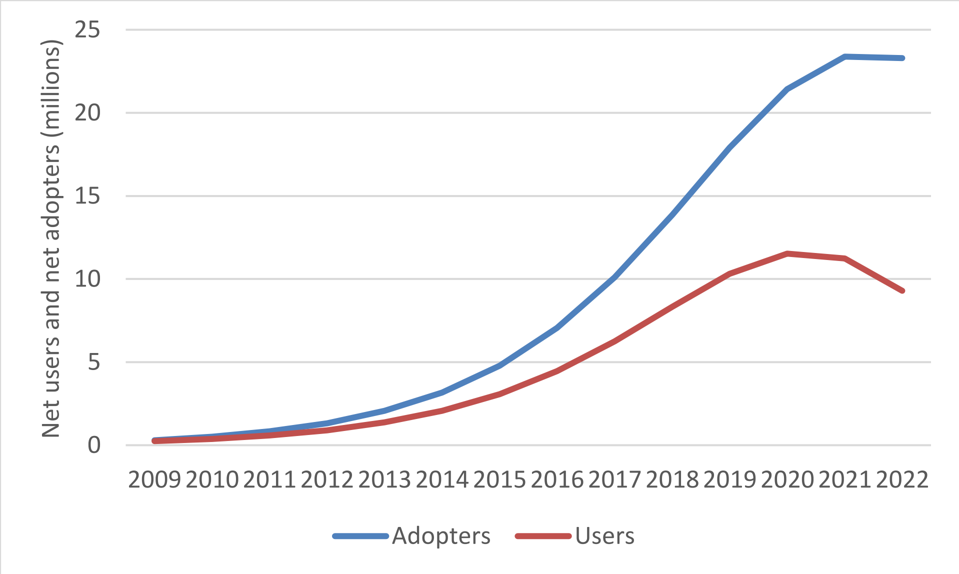
Note that the net addition to the number of Roku users (net users) in 2022 is almost 10m. However, during this year, a total of 14m users left the service, as the churn rate is about 20%. Thus during 2022, about 24m new customers bought the Roku hardware device. Yet if we count the number of users, who bring about the bulk of Rokus revenues (87% 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

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

adopters (2021) is ***later*** than the peak of the number of new users (2020). We subsequently show that this is a general case and not specific to this dataset and that this difference increases with increasing churn.

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



* Source: Roku annual reports and Statista

While Roku is a good example in light of the transition from products to XaaS, most XaaS growth patterns such as those of many DTC subscription firms, do not include a durable part. As the durable part is well-known and heavily researched, we focus on pure XaaS growth and first need to specify the model used to describe users' growth. Our model is based on a service growth model suggested by Libai, Muller and Peres (2009) which considers customer churn as an integral part of the growth process[4]. 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:

[4] 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.

(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[5]:

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

4. The growth of users

Recall that the XaaS growth model generates four curves of interest: Adopters, net adopters, users and net users. While the adopters' and net adopters' growth patterns have been much analyzed in the diffusion literature, we have limited intuition on the users' and net

[5] 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.

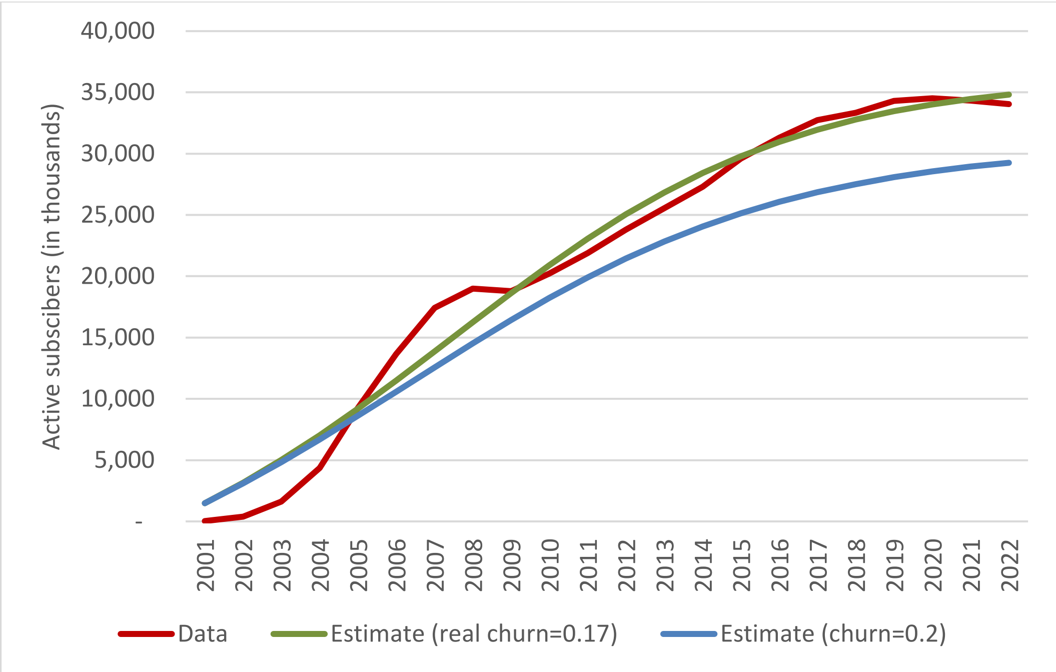
users' curve patterns. In this section, we explore these curves and make several propositions regarding their patterns. To do so we use both analytical proofs and simulations. For all the simulations we define the parameters of interest with diffusion parameters in the range $0.001 \leq p \leq 0.07$, 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 as the "user potential," which corresponds 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:

First, this is the user base - $x(t)$, that is s-shaped, yet it can decline temporarily. This is an important difference from the old economy with sales of durables. A reason 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 that can decline for a number of reasons such as an economic downturn, or a sudden increase in churn, or just bad publicity with the brand. Note that we have modeled a constant churn for simplicity but both a dynamic churn and a dummy variable for the economic conditions could be added to the equation[6]. In Figure 3 we see two such occurrences at 2008-2009 and 2021-2022, both occur because satellite radio is highly correlated with car ownership and in these periods car sales and ownership suffered.

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



* Source: Annual reports of XM, Sirius and SiriusXM

Second, in the last four years, users have hovered just below 35m. 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 36.2m users. Of course, many more cars are registered in the US (about 290 million), but what the data are telling us is that the 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 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

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

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 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. To assess the magnitude of the effect, we can compute the sensitivity of the user potential to churn in a standard elasticity setting: The percent decline in users' potential as a result of an increase of 1% in churn $\left(-\frac{\partial \bar{m}}{\partial \delta} \cdot \frac{\delta}{\bar{m}}\right)$. It is straightforward to compute this elasticity in the SiriusXM case to be 0.78, that is, a one percent increase in SiriusXM's churn rate will decrease the user potential by about 0.8%.

The peak of net users

In Figure 3 we present the hypothetical case of an increase of the churn rate from the current 16.6% to 20%. This increase of about 20% resulted in a decrease of about 14% in the user potential, from 36m to 31m, quite a significant drop. To have a feel for the general case, Table 2 summarizes the churn rate and elasticity of user potential related to churn in selected XaaS firms.

Table 2: Churn rate and elasticity of effective user potential to churn in selected XaaS firms*

XaaS Firm	Churn rate (annual)	Elasticity of user potential to churn**
Peloton	10.9%	0.12
Roku	20.0%	0.36
SiriusXM	16.6%	0.78
Spotify (premium)	17.9%	0.37

* Sources: Statista; annual reports of Peloton, Roku, and SiriusXM
** Percent decline in user potential as a result of a 1% increase in churn

Note that although these elasticities appear to be small, they do have a significant effect on the user potential. Take Spotify as an example. An increase of churn from the current 18% to 19%, reduces the user potential by 4 million users from its current 240m potential. These are 4m potential premium users that Spotify will never see, nor enjoy their lifetime value, regardless of their expected retention rate and listening habits.

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 it takes to get to it 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 the net user curve.

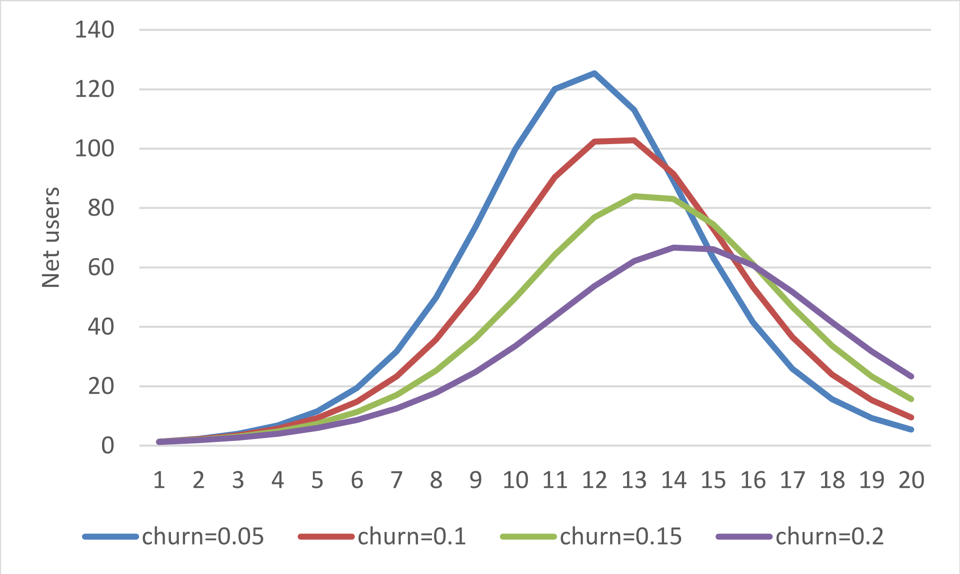
Recall the finding of Figure 1 that the peak in the number of Roku's net adopters (2021) is ***later*** than the peak in the number of new users (2020). We argue that it is not specific to Roku, as demonstrated in the next proposition, proven in Appendix A.

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. This 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.

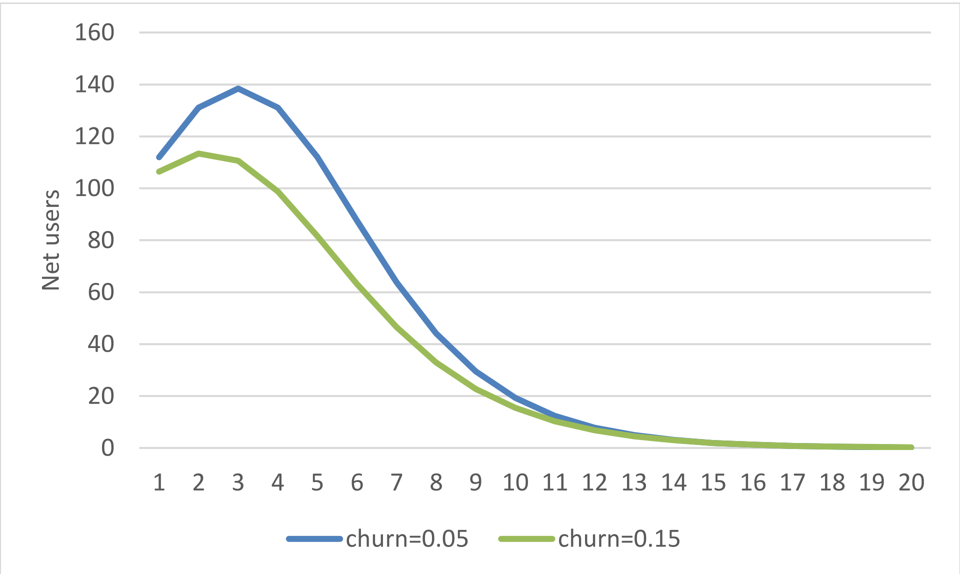
To further look at the net user curve, consider Figure 4, in which we observe the growth curves of net users for various churn rates. We observe a decline in the peak of net users and an increase in the time at which this peak is achieved. The significant drop of the peak of the number of new users in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

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: $p = 0.1, q = 0.4, m = 1{,}000$

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 an early skewed growth, this pattern reverses, and the contagion coefficient slightly declines while the external coefficient sharply increases, leading to the pattern of Figure 5. We thus summarize these findings by the following proposition:

Proposition 3: With an increase in 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 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 so can 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, such as the entertainment industry, it has been observed that the adoption curve can instead monotonically decline over time, resembling an exponential decay. 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, coupled with the wide availability of screenings upon release and the viewers' inclination to be the first ones to see the movie, often leads to an initial surge in demand.

The case of movies may be only part of a broader phenomenon that will affect the user curve's shape. Classic diffusion modeling assumes that social influence (whether it is word of mouth, imitation, or network effects) starts when the product is launched. This creates the left tail, leading to the adoption bell shape (Rogers 2003). However, we see increasing evidence where the social influence part of the customer life cycle precedes initial acquisition. Online sources and particularly social media outlets enable users to be exposed to information, discuss and create social influence before the new product is launched (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, a considerable mass of customers will adopt the product as it is launched. This will affect the adoption curve and, consequently, the user curve. Here we do not get into the dynamics of the social influence process, and we 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 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.

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 key 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, taking into account the changes in revenues 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 more adopters come onboard, 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), commonly used to assess the success of new technological ventures (Ofek, Libai and Muller 2022).

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). 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

[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. We deal with this point shortly.

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).

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). We 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 based on the CLV and ARR approach: 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).

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

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 $\text{ARR} = \text{ARPU} \cdot x(t)$. There are two modifications required for this analysis: First ARR usually takes into account changes in ARPU, while we assume, as is the standard in customer equity calculations, a constant ARPU and costs[8]. Second, in order to calculate equity, we subtract the average costs of serving the customer 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 get 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 5a: With an infinite horizon, the ARR and CLV based customer equity yield the same result, that is Equations 9 and 10 are equivalent.

Proposition 5b: With a finite horizon, the CLV methods yields a higher value than the ARR approach that more accurately reflects the true customer equity.

From the traditional infinite perspective, it becomes clear that irrespective of the approach used to analyze the stream of revenue, the results are identical. However, investors and firms may not always work within an infinite timeframe, instead focusing on customer profitability over a defined number of years. Within the context of a defined timeframe, differences between the methodologies begin to emerge. Even when the number of cohorts under

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

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), 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 with a different scale.

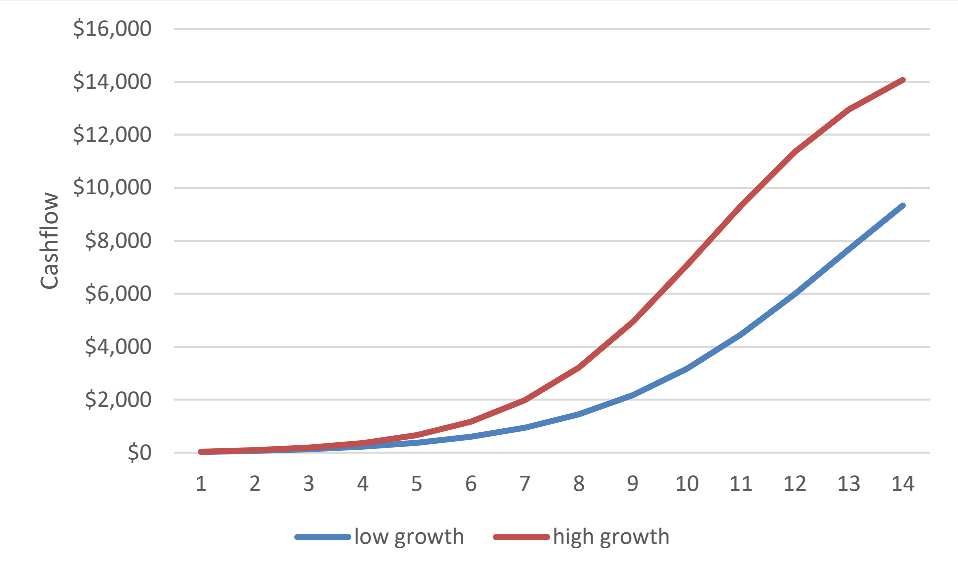
However, if customer acquisition costs are factored in - a step necessary for a comprehensive monetary view - the shape of the curve can undergo a fundamental change. This is due to the possibility of several periods passing before acquisition costs are recovered. As more customers are acquired, the 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 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 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 6a 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. 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's 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.

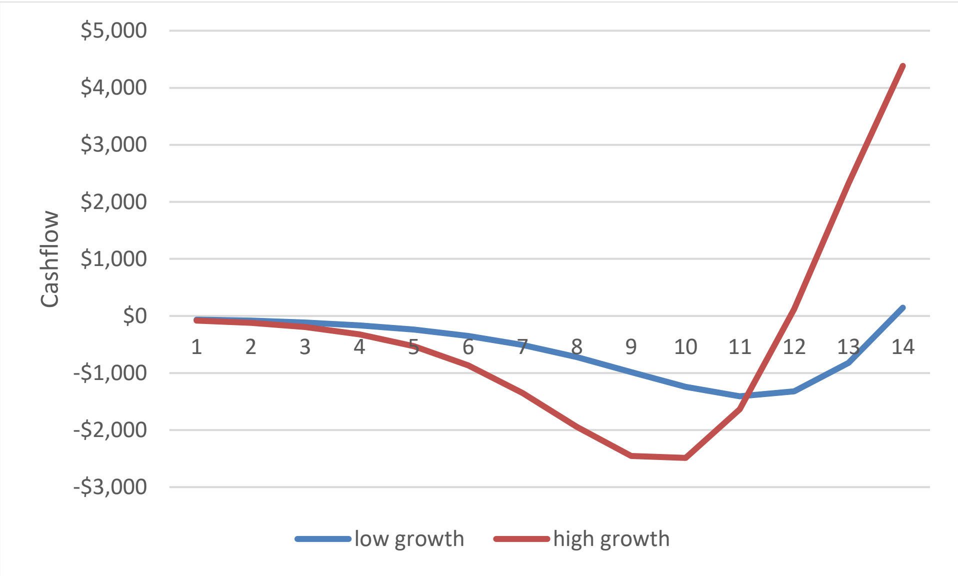
Define the ***cashflow trough*** as the maximum negative cashflow of the new venture (Skok 2017). For example, in the simulation leading to Figure 6b, the maximum negative cashflow of the fast growth is \$2,488, while the corresponding one in the slow growth is only \$1,408. Skok argues that for a fast-growing 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 (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 6.

Figure 6a: 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 6b: 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 6: Faster customer acquisition causes the magnitude of the cashflow trough, that is the maximum negative cashflow, 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 reality of the trough 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. It is understandable why it is well accepted by academics (Gupta, Lehman and Stuart 2004). 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

To underscore the relevance and significance of the topics addressed above, we ponder 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 over the past, 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 need to allow for comparability, transparency, and comprehensive quantitative analyses. We propose that our XaaS growth framework offers an appropriate blueprint. The central issue is how to maximize customer equity, with different strategies that could rely on either the Annual Recurring Revenue (ARR) or Customer Lifetime Value (CLV) - both of which are 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 money. 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's not readily apparent to the firm - it never registers in the books, leaving the firm unaware of the lost potential customers. We propose that this covert indirect churn effect could be as substantial as the cash flow loss from churning customers.

Table 3: 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 demonstrate this via Table 3: Consider first columns II and V of the table 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 17 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 of the table) 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. 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% ($\overline{m} = 635$)? This will yield the loss due to a decrease in user potential net of the increase in churn. The table 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%.

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 considered. A comprehensive examination requires analysis 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 has its churn that 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 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 (NDT) instead or in addition to the measure of customer retention. NDT is based on the ARR curve and represents the rate of change in 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 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

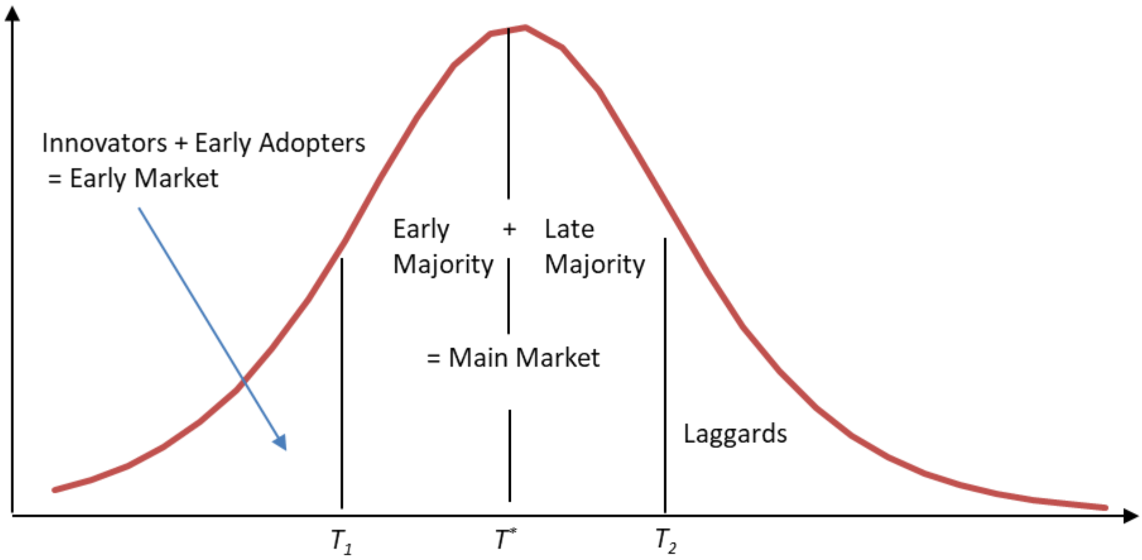
100% (Heymann 2023). Practically, various SaaS firms have stopped writing customer churn rates in their financial reports, disclosing (if they do) only NDR.

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. In a general sense, 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.

Adopters categories

In light of the focus of traditional new product frameworks on first adoption, the move to XaaS thinking requires updating the fundamental thoughts on the diffusion of innovations. A relevant example is 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 7:

Figure 7: Adopter Categories



In the XaaS context, we can ask an analogous question. If we look at a product life cycle of a XaaS product, such as one of the growth curves of Figure 4, how many, or what's 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 - from the first to the second inflection point.

We find (in Appendix A) that with an increase in churn, the relative size of the early market declines while the relative size of the 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 the second inflection point is later, causing the main market to increase. Indeed, 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.

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 allows 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.

Conclusion

Marketing researchers should update their thinking of new product growth models to stay relevant for contemporary managerial practice. We believe that moving to XaaS dominant markets is a challenge but simultaneously offers a rich spectrum of opportunities. A careful, empirically supported analysis should follow the above exploratory propositions and demonstrations to create a more holistic view of XaaS growth. 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 the proposition in the discussion (denoted in this appendix as Proposition 7). 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 that $\bar{q} \geq 0$.

Lastly, elasticity of $\bar{m}$ with respect to δ is given by:

$$(10)\ \eta = -\frac{\partial \bar{m}}{\partial \delta} \cdot \frac{\delta}{\bar{m}} = \frac{m}{2q} \cdot \left(\frac{\Delta + \beta}{\Delta}\right) \frac{2q}{m(\Delta + \beta)} \delta = \frac{\delta}{\Delta}$$

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:

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

Differentiate Equation 11 to verify that when $d^2x/dt^2 = 0$, $d^2a/dt^2 = \delta dx/dt > 0$.

Proposition 5: Customer Equity of a XaaS firm is given by either the CLV method (Equation 12) or the ARR method (Equation 13). 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.

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

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

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

$$(14)\ \pi = \int_0^\infty CLV \cdot \frac{da}{dt} \cdot e^{-it} dt = CLV \cdot \int_0^\infty \left\{\frac{dx}{dt} + \delta x(t)\right\} \cdot e^{-it} dt$$
$$= \frac{g}{(i+\delta)} \cdot \int_0^\infty \left\{\frac{dx}{dt} + \delta x(t)\right\} \cdot e^{-it} dt$$

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

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

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:

$$(16)\ \pi = \frac{g}{(i+\delta)} \cdot \int_0^\infty \left\{\frac{dx}{dt} + \delta x(t)\right\} \cdot e^{-it} dt$$
$$= \frac{g}{(i+\delta)} \cdot \int_0^\infty \{ix(t) + \delta x(t)\} \cdot e^{-it} dt = g \cdot \int_0^\infty x(t) \cdot e^{-it} dt$$

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: $\int_0^T CAC \cdot \frac{da}{dt} \cdot e^{-it} dt$.

$$(17)\ \pi_{CLV,T} = \int_0^T CLV \cdot \frac{da}{dt} \cdot e^{-it} dt$$

$$(18)\ \pi_{ARR,T} = \int_0^T g \cdot x(t) \cdot e^{-it} dt$$

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,

$$(19)\ \pi_{CLV,T} = \frac{g}{(i+\delta)} \cdot \int_0^T \left\{\frac{dx}{dt} + \ \delta x(t)\right\} \cdot e^{-it} dt$$
$$= \frac{gx(T)e^{-iT}}{(i+\delta)} + \frac{g}{(i+\delta)} \cdot \int_0^T \{ix(t) + \ \delta x(t)\} \cdot e^{-it} dt = \frac{gx(T)e^{-iT}}{(i+\delta)}$$
$$+ g \int_0^T x(t) \cdot e^{-it} dt = CLV \cdot x(T) \cdot e^{-iT} + \int_0^T g \cdot x(t) \cdot e^{-it} dt$$

It follows that,

$$(20)\ \pi_{CLV,T} = CLV \cdot x(T) \cdot e^{-iT} + \pi_{ARR,T}$$

And thus,

$$(21)\ \pi_{CLV,T} > \pi_{ARR,T}$$

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.

Proposition 7: 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 7 in the main text):

$$(22)\ T_1 = +\frac{1}{\bar{p}+\bar{q}}\ln\left(\frac{\bar{q}}{\bar{p}\cdot\left(2+\sqrt{3}\right)}\right) = T^* - \frac{1}{\Delta}\cdot\ln(2+\sqrt{3})$$

$$(23)\ T_2 = +\frac{1}{\bar{p}+\bar{q}}\ln\left(\frac{\bar{q}\cdot\left(2+\sqrt{3}\right)}{\bar{p}}\right) = T^* + \frac{1}{\Delta}\cdot\ln(2+\sqrt{3})$$

$$(24)\ T^* = +\frac{\ln\left(\frac{\bar{q}}{\bar{p}}\right)}{(\bar{p}+\bar{q})} = \frac{1}{\Delta}\cdot\ln\left(\frac{\Delta+\beta}{\Delta-\beta}\right)$$

For T^* to be nonnegative, we need the log in the RHS of Equation 24 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:

$$(25)\ M = \frac{1}{\sqrt{12}}\cdot\frac{2\Delta}{\Delta+\beta}$$

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

$$(26)\ \frac{\partial M}{\partial\delta} = -\frac{\partial M}{\partial\beta} = -\frac{2}{\sqrt{12}}\cdot\frac{(\Delta+\beta)\cdot\frac{\partial\Delta}{\partial\beta} - \Delta\cdot(\frac{\partial\Delta}{\partial\beta}+1)}{(\Delta+\beta)^2} = -\frac{2}{\sqrt{12}}\cdot\frac{\beta\cdot\frac{\partial\Delta}{\partial\beta}-\Delta}{(\Delta+\beta)^2}$$

Using Equation 8 we have:

$$(27)\ \frac{\partial M}{\partial\delta} = -\frac{2}{\sqrt{12}}\cdot\frac{\beta^2-\Delta^2}{\Delta(\Delta+\beta)^2} = +\frac{2}{\sqrt{12}}\cdot\frac{\Delta-\beta}{\Delta(\Delta+\beta)} \geq 0$$

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:

$$(28)\ T_2 - T^* = T^* - T_1 = \frac{1}{\Delta}\cdot\ln(2+\sqrt{3})$$

$$(29)\ \partial(T_2 - T^*)/\partial\delta = \partial(T^* - T_1)/\partial\delta = \ln(2+\sqrt{3})\cdot\frac{\beta}{\Delta^3} \geq 0$$

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

$$(30)\ E = \frac{1}{2}\cdot\left(1-\frac{\Delta-\beta}{\Delta+\beta}\right) - \frac{1}{12}\cdot\left(1+\frac{\Delta-\beta}{\Delta+\beta}\right) = \frac{5}{12} - \frac{5}{12}\cdot\frac{\Delta-\beta}{\Delta+\beta}$$

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

Using equation 8 we have:

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

Appendix B

This 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 $\rho = 0.21$*** and the correlation between q and the proportion of cases of increasing churn is $\rho = 0.86$***.

Figure B1:

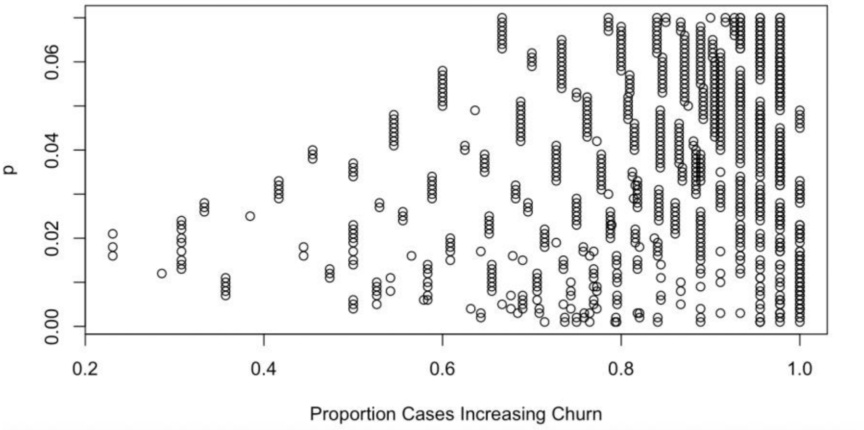
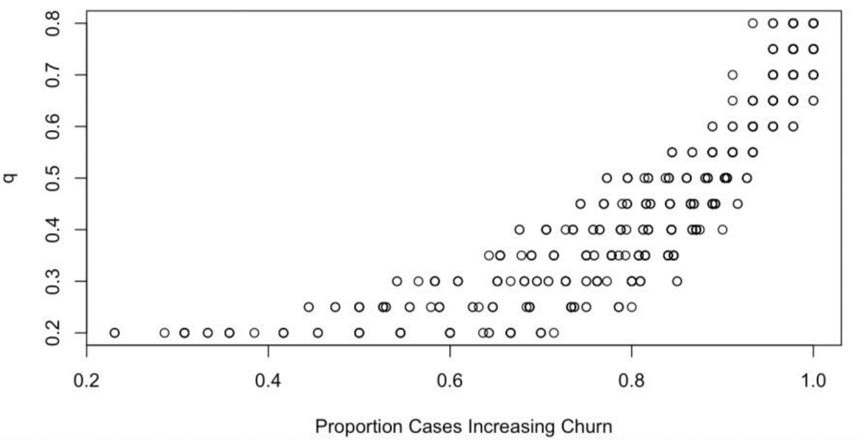
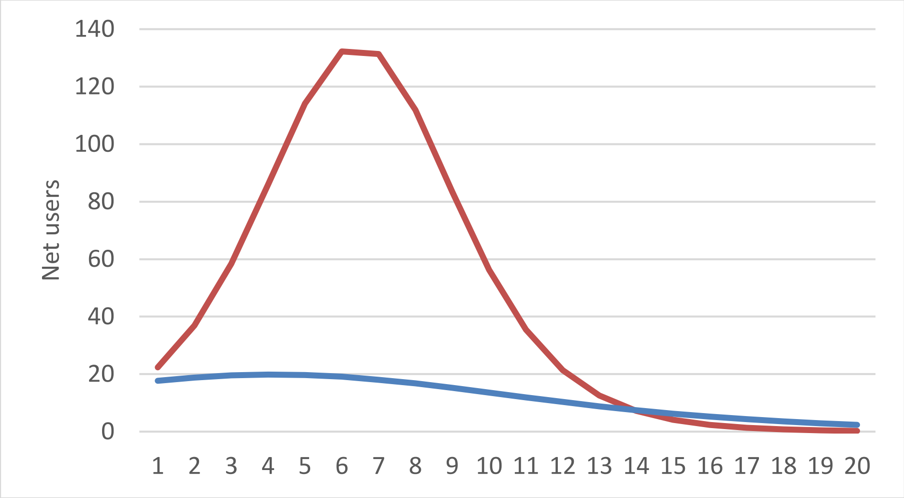


Figure B2:



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.

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