User-Based Valuation of Digital Business Models

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Abstract: The digital economy represents major challenges for established corporations around the world. To succeed in this rapidly changing environment, it is no longer sufficient to compete by incremental product or process innovation. Achieving sustainable competitive advantage requires managers to exploit the disruptive potential of emerging technologies to transform business models, value chains or entire markets. Since the global deployment of the internet and other digital technologies, a new class of business models has emerged. Often, these business models are based on digital products and services, offered and distributed via digital distribution channels. Successful players such as Google and Amazon that have only existed a few decades are now among the most valuable companies in the world. Standard company valuation methods such as the Discounted Cash Flow (DCF) technique are based on traditional financial metrics that often fall short in explaining the high market capitalizations of user-based businesses. We propose a stochastic user-based company valuation model, that is able to forecast user development, estimate customer lifetime values and customer equity and link it to the value of a digital business. We apply the model to the real-world business case of Netflix and show that the customer equity estimations from our model track the market capitalization of Netflix remarkably well.

Keywords: Digital Business Models; Customer-based Company Valuation; Growth Option; Stochastic Logistic Growth Model

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1 Introduction

The digital economy has become a frequent keyword in recent publications on management and information systems. The term describes an economy that is based on the digitization of information and the respective information and communication infrastructure. It refers to the phenomenon that the way, in which economic values are created, produced, distributed and exchanged, changes fundamentally in the digital economy [30]. In the digital economy, technological developments are not gradually increasing but skyrocketing exponentially. Living in a world determined by exponential change entails extensive implications for society, politics and the economy. When it comes to aligning businesses, facing these developments is no longer about simply digitizing business processes; it is about transforming business models to maintain sustainable competitive advantage. It is about creating something new, rather than just soliciting a process of adaption. In the near future, industry leaders, even in traditional industries such as automotive or financial services, will be tech companies. Additionally, traditional corporations are increasingly converting into tech companies, as the economy and the business environment further digitalizes.

In this context, the business model has become a frequently applied tool to analyze corporate strategies and the business environment and identify new opportunities for business model innovation. The business model describes the rationale of how an organization creates, delivers, and captures value [19]. The different components of a business model can be summarized by the four questions "who?", "what?", "how?" and "why?" [10]. The answers to these questions concretize the business model's customer segment, its value proposition, the value chain and the revenue model. New types of business models have emerged as a consequence of the increasingly digitalizing economy. In contrast to traditional asset-based business models that are built around linear value chains, the class of digital business models is typically based on digital products or services advertised, offered and distributed via digital channels such as online platforms and mobile applications. In recent years, we could witness strong economic success of these types of businesses. Successful innovators such as Amazon, Google, Microsoft, Apple, Uber, Airbnb, eBay or Salesforce that have only existed a few decades are now among the most valuable companies in the world [1]. From a managerial standpoint, digital business models have some crucial advantages over traditional asset-based business models:

- unlimited scalability,
- extremely low marginal costs,
- no physical proximity to customers,
- close-to-zero transactional friction,
- global reach via digital distribution channels and the internet,
- high-paced product innovations,
- high potential of automation to increase efficiency,
- high transparence based on automatically generated process- and customer-related data,
- high levels of flexibility and rapid reaction times,

- low capital expenditures and overhead costs.

Among digital business models, Moazed and Johnson [18] further distinguish linear business models and platform business models. While linear businesses create a product or service and sell it to the customer, platform businesses function as an intermediary between one or more groups of producers and consumers. Thus, platform businesses do not create any of the products or contents offered on their platform. They simply provide the infrastructure to enable efficient matchmaking between buyers and sellers. Another important point for distinguishing business models is their approach to monetization. In both, linear as well as platform business models, there are subscription-based, Freemium and transactions-based business models. Sometimes, we can also find hybrid monetization mechanisms. Table 1 provides a high-level summary of the different types of digital business models.

With linear digital business models, content is produced or provided by a single producer, who distributes its services or products via digital channels. On digital platforms, content is produced or provided by a large number of producers, who are independent of the platform provider. With some platforms, buyers and producers represent a homogeneous group (e.g. social media and dating platforms). Other platforms such as Uber and Airbnb, are used by a heterogeneous group of producers and sellers (e.g. drivers and passengers, landlords and tourists). A major difference between linear digital business models and digital platforms is that the value provided by platforms is highly dependent on network effects. A larger number of consumers on the platform will increase the value to producers and thus lead to a larger number of producers and vice versa. Network effects can explain the winner-takes-it-all phenomenon, which we can often observe with successful platforms, such as Amazon and Facebook. After the so-called critical mass of users is reached, user growth usually becomes self-sustaining as the high network value attracts more and more new users. This phenomenon might be one factor in explaining the huge success of famous platforms and their high enterprise values.

Figure 1 shows some example firms with different linear and non-linear business models and their current market capitalization. It suggests a big difference between the valuation of large traditional incumbents and digital innovators. The chart shows that company age and level of net income are not necessarily good indicators for market capitalizations. Most of the illustrated linear incumbents have been market leaders in their industry for several decades. However, these companies' valuations are significantly smaller than the market capitalizations of successful platforms such as Amazon, Alibaba, Facebook, Google or Apple. Even Netflix, which has almost zero fixed assets and shows a significantly lower net income than the incumbents, exhibits market capitalization of 163 billion US-dollars. Additionally, digital companies such as Dropbox and Spotify, who have not made a single dollar of profit in their firm histories, are worth 24 billion and 10 billion US-dollars. Market capitalization is a popular indicator for company valuation. The difference between this metric and the total enterprise value is the cash and short-term investments minus the total debt of a company. Thus, market capitalization a crucial indicator for the total value of a company. Traditional company valuation techniques such as the enterprise discounted cash flow (DCF) or multiple methods are based on metrics from financial statements and have difficulties when valuing digital business models. While financial statements can certainly serve as a proxy for a digital company's performance, we should identify the most important value drivers that directly influence the performance of digital business models.

	Monetization	Description	Typical examples
Linear Digital Businesses	Subscription-based	Products & services are created or acquired by the company and provided to the customer, who pays a fixed subscription fee.	Netflix
	Freemium	Products & services are created or acquired by the company; there are two different versions of the product; a standard product for free users and a superior product for premium users; often these companies include ads to generate additional revenue streams from free users.	Spotify
	Transaction-based	Products & Services are created or acquired by the company; the company offers, sells or grants temporary usage of the product for a certain fee.	Software as a Service such as Salesforce, car sharing companies such as ServiceNow
Digital Platforms	Free	Contents are not owned by the platform; access to and usage to products and services are free; revenues are generated by secondary revenue streams such as integrated ads, offerings by third parties or commercialization of user data.	Social media platforms such as Facebook and Instagram, Messaging services such as WhatsApp and Line
	Premium	Contents are not owned by the platform; access to and usage of the platform are granted for a fixed subscription fee; often only the producers are charged while consumers can access for free.	WooCommerce, Shopify
	Freemium	Contents are not owned by the platform; a standard product for free users and a superior product for premium users is offered on the platform; often ads are included to generate an additional revenue stream from free users.	LinkedIn, Dropbox, Skype, Tinder
	Transaction-based	Contents are not owned by the platform; many producers offer their products and services to many consumers on the platform; the platform provider typically earns a fee for every successful transaction.	Airbnb, Uber, Amazon, PayPal, eBay, Alibaba

Table 1: Overview of Digital Business Models

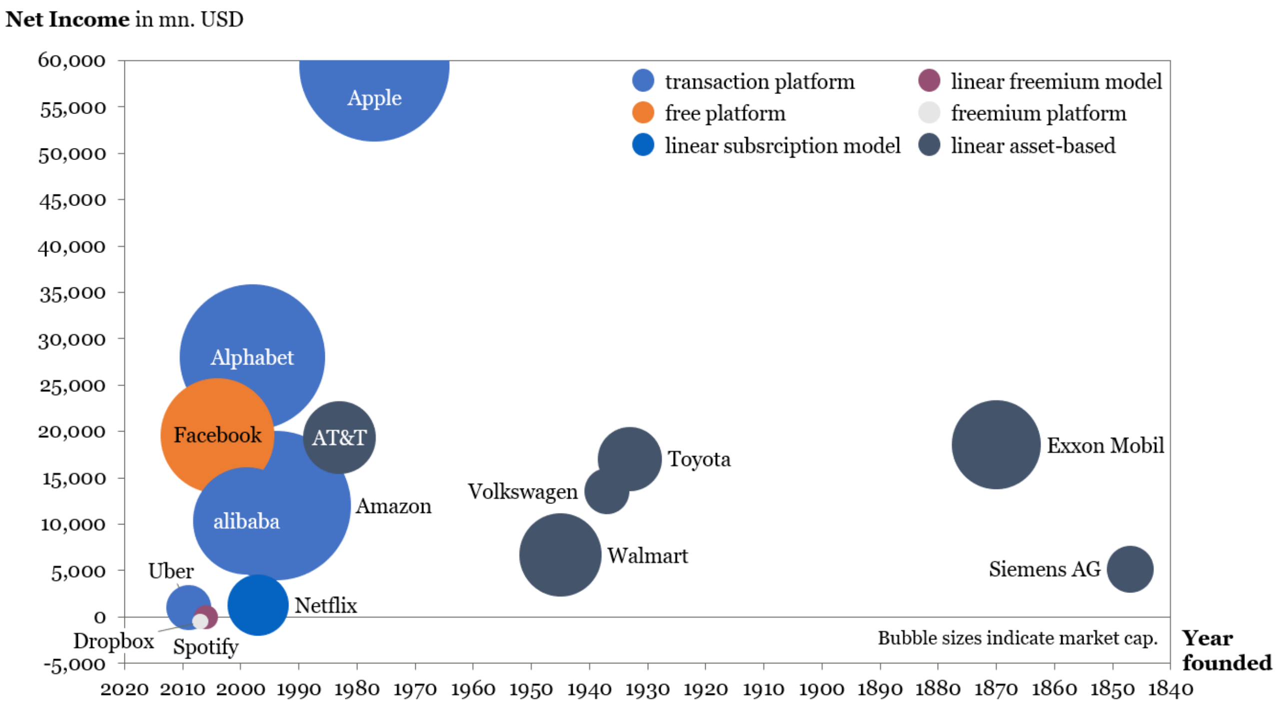

Figure 1: Example market capitalizations of different types of business models

2 Customer-based Company Valuation

A digital company's customers are users. User behavior drives the profitability of a digital business model. Since the global deployment of the internet and the associated emergence of digital business models, a large number of new performance measures have been introduced in academic literature and managerial practice alike. While these metrics are derived from traditional performance measures such as revenues, net income or the return on invested capital, mapping then to users is a helpful tool for understanding a digital business's revenue mechanics and increase transparency for value-based management. While, as outlined in table 1, different approaches of monetizing users exist in digital business models, there are critical metrics that can be applied for all types of digital business. In this context, a frequently applied metric is the average revenue per user (ARPU). It shows how much revenue a single user generates on average and, thus, the incremental revenue of acquiring new or losing existing users. The gross margin multiplied by the ARPU then reflects the gross profit per user. Another important metric is the cost of user acquisition (CAC). It shows you how much the company has to spend on marketing and sales to acquire one new user. In order to be profitable, the company's CAC should be significantly lower than the ARPU. Regarding future performance, the net growth rate of the user base is important. The net growth of users in a certain period is the sum of all newly acquired users minus the users who have churned. In order to have positive net growth, the number of churns has to be smaller than the number of acquisitions.

With the growing importance of digital business models and the increasing popularity of customer-centric management, the customer lifetime value (CLV) has gained importance. It is a concept that has originated from marketing, but has grown into an important metric for strategic management of digital businesses. The customer lifetime value is the sum of all discounted net cash flows of one user, or a cohort of users. Customer equity (CE) can then be calculated as the sum of all CLVs over all existing and future users. In academic literature, several approaches exist that link CLV and CE to company valuation. Srivastava et al. [25] were the first marketing academics to recognize the potential for using some of the models of customer behavior to generate key insights for estimating cash flows. Gupta et al. [13] labeled these valuation approaches as the family of customer-based company valuation (CBCV). CBCV describes the process of valuing a firm by forecasting current and future customer behavior using customer data in conjunction with traditional financial metrics [16]. For many firms, customer equity represents a major share in shareholder value enabling the link between user behavior and enterprise valuation [16]. A vast number of scholars have published articles that further analyze this link ([3]; [2]; [12]; [17]). Most of these articles focus on contractual (i.e. subscription-based) monetization examples, as user-behavior modeling can be modeled by fixed revenue streams and easy to observe retention rates [17]. However, more recent studies have also started to value transaction-based business models by applying CLV techniques. For example [14] use probabilities of a customer to purchase in a certain time period to calculate the customer equity and link it to a firm's market capitalization.

A number of articles apply their CLV models to digital companies such as Netflix [29] and XING.com [11]. Digital business models are especially suitable for customer-based company valuation as user bases are typically large, exhibit high growth rates and easily observable purchase behavior. Thus, users are a digital company's most valuable asset and the main value driver for enterprise value. Shapiro et al. [24] show that the number of customers in prosperous new technology companies, especially in internet-based companies, increases exponentially in the first few years of the company's existence. After a while, growth rates start to decrease gradually until an upper asymptotic limit of total potential users is reached. This phenomenon can be often observed in natural growth dynamics, such as biological population growth ([21, 27]), technological progress ([8, 7, 9, 28]), new product deployment ([15]) or dynamics in production volumes ([6]). Logistic growth curves are often applied to forecast these dynamics based on historical data. Accordingly, several scholars use logistic growth curves to model customer growth across time. For example Cauwels and Sornette [5] use a logistic growth curve to model the growth of Facebook users. Gupta et al. [13] use logistic user growth to link the customer equity of one traditional company (Capital One) and four internet firms (Amazon, Ameritrade, eBay and E*Trade) to their market capitalizations. Their results show that estimates of their customer value are reasonably close to current market valuation.

Existing research mostly uses deterministic logistic growth curves to model user dynamics. However, this approach has some critical limitations as it explicitly assumes that future user growth is known. This fairly unrealistic assumption can be relaxed by including uncertainty. There are several ways to include uncertainty with logistic growth models: add uncertainty about the total number of users, add uncertainty about user growth rates or add uncertainty about the asymptotic limit of total users. The difference between these approaches is basically a modeling issue, as all three relate to uncertainty about the number of users across time. Literature provides several stochastic approaches to company valuation. Most are related to the Real Options approach, that can value managerial flexibility in investments under uncertainty. For example Schwartz and Moon [22, 23] value high-growth internet companies by modeling the traditional DCF as a growth option under three sources of uncertainty. Similarly, Perotti and Rossetto [20] value internet portals as a portfolio of real options. Both studies argue that Internet companies have call-option characteristics since they have large potential upside and limited downside potential (i.e. bankruptcy). From a CBCV perspective, we only know of a single article that is based on stochastic logistic growth dynamics. Tallau [26] includes several sources of uncertainty relating to the number of customers, the average revenue per user and the variable costs of a company. The author further assumes that the number of users evolves based on the Bass model (Bass 1969), which is a famous mixed-influence model for logistic growth that distinguishes two groups of new adopters, namely innovators and imitators. However, due to the model's complexity, it requires estimation of 32 different input variables, which are mostly not observable limiting the use for accurate practical application. In the next section, we develop a simple stochastic customer equity estimation model for subscription-based digital business models. After developing the model, we apply it to the example of Netflix, and show how the required input parameters can be obtained.

3 Model development

Consider an existing company with a subscription-based digital business model. The revenue mechanics of such a company are driven by the number of subscribing users and the revenues per subscribing user. The number of future users depends on three variables: the number of existing users, the number of newly acquired and the number of churned users. We consider a company with an existing and self-sustaining user base. The churn rate is equal to one minus the retention rate and the number of newly acquired users is the net growth of the user base minus the number of churned users in the same time period. Thus, we can model the growth of the user base based on a birth-death population growth model, which can be often found in mathematical biology [4]. The growth dynamics are logistic, as the user base cannot grow infinitely large. The upper limit of the total number of subscribing users can be interpreted as the total number of all potential users across all relevant markets (e.g. all households with internet access).

We assume that the total number of paying users follows a simple differential logistic growth equation

$$dU_t = (a_t - c_t)U_t(\frac{1 - U_t}{K})dt,$$

while a_t is the instantaneous acquisition rate (or birth rate) relative to the user base U_t, c_t the instantaneous user churn rate (or death rate) and K the theoretical asymptotic limit (or carrying capacity) of total users at the end of the regarded time horizon T.

We include two sources of uncertainty in our model. The first is uncertainty about the number of newly acquired users represented by the stochastic acquisition rate

$$da_t = \mu^a a_t dt + a_t \sigma^a dW_t^a,$$

while μ^a is the expected change in a_t, σ^a its volatility and dW_t^a the Wiener increment. The second is uncertainty about the number of users, who cancel their subscription, modeled by the stochastic churn rate

$$dc_t = \mu^c c_t dt + c_t \sigma^c dW_t^c,$$

while μ^c is the expected change in c_t, σ^c its volatility and dW_t^c the Wiener increment. Thus, acquisition rates and churn rates evolve following geometric Brownian motions.[1]

The diffusion terms of a_t and c_t are assumed to be correlated. That is,

$$dW^a dW^c = \rho dt,$$

while ρ is the coefficient of correlation between the two Wiener increments dW^a and dW^c. Thus, variations in acquisition rates will likely result in variations in churn rates and vice versa.

The discounted customer lifetime value of the customer cohort at any time t can then be calculated by

$$\mathrm{CLV}_t = (\pi \mathrm{ARPU} U_t - \mathrm{CAC} a_t U_t - F)(1-\tau)(e^{-rt}),$$

while π is the company's gross margin, ARPU is the average revenue per user, CAC is the cost of acquiring a new user, F is the company's fix costs, τ the corporate tax rate and r the company's weighted average cost of capital (WACC). The total customer equity can then be determined by computing

$$\mathrm{CE} = \int_0^T \mathrm{CLV}_t dt + \frac{\mathrm{CLV}_T(1+g)}{r-g},$$

while g is the terminal growth rate of customer lifetime values beyond T. The last term of this equation is a perpetuity, which is commonly applied in calculating terminal values for company and project valuation. Thus, the customer equity is the net present value of all cash flows created by existing and future users. It describes the net worth of a company's current and future user base.

We use Monte Carlo simulation to approximate the continuous-time model by choosing an integer m so that the time span $[0,T]$ is divided into m intervals whose length is $\delta t = \frac{T}{m}$. We chose T and m in a way to discretize the continuous-time model to generate periodic (e.g. monthly, quarterly, annual) state variables and compute the present value of the sum of all periods $\{[t_n, t_n + \delta t] \in [1, T]\}$. The state variables are simulated by generating N sample paths for values of $a_t(\omega), c_t(\omega), U_t(\omega)$ and $\mathrm{CLV}_t, \omega \in [1, 2, \ldots, N]$ restricted to the discrete set of dates $t_1 = \delta t, t_2 = 2\delta t, ..., T = m\delta t$. The CE expectation can then be calculated by averaging the discounted sum of the CLV sample paths

$$\mathrm{E}^P[\mathrm{CE}] = \frac{1}{N} \sum_{\omega=1}^{N} \sum_{t=\delta t}^{T} \mathrm{CLV}_t(\omega) + \frac{\mathrm{CLV}_T(\omega)(1+g)}{r-g},$$

In order to arrive at the value of the firm, we would have to include changes in working capital, depreciation and net capital expenditures. However, as digital companies typically have fixed assets and depreciations that are negligibly low, we refrain from including these metrics in our estimation.

[1]Geometric Brownian motions have the implicit assumption that the state variable can never be negative. While the net user growth rate can be negative, that is, in case the churn rate is higher than the acquisition rate, positive acquisition and churn rates are a desirable assumption. Geometric Brownian motions are a widely applied concept in finance, for example when modeling stock price diffusion, which is why we refrain from explaining this concept at this point.

4 Numerical application - the case of Netflix

In order to find out how well the presented CE-model tracks the value of digital subscription-based companies, we apply the model to the case of Netflix and compare the resulting CE estimation with the respective market capitalization. Netflix presents a good example, as it is a very successful subscription-based provider of digital contents and publicly traded, which makes most input parameters directly observable or calculatable from publicly disclosed data. As financial results are disclosed quarterly, we discretize on a quarterly basis. We present how to obtain the input parameters for Q1 2019, forecast CLV development and estimate the resulting customer equity. In a second step, we run back testing by conducting the same computation for all quarters from Q1 2013 to Q4 2018, in order to analyze how well our CE model is able to track the market capitalization across time. This provides us with a total of 25 CE estimates, which will help us to more reliably determine the accuracy of our model. Table 1 shows all input parameters for the simulation of Q1 2019.

Number of subscribed users: this parameter is publicly available and can be extracted from Netflix's quarterly reports.

Acquisition and churn rates: unfortunately, Netflix has stopped disclosing its churn rates in 2010. However, the net growth rate of the user base is observable. Between 2013 and 2019, the average annual growth rate lied between 25 and 30 percent. The net growth rate is the acquisition rate subtracted by the churn rate. So, if we assume the churn rate to amount 10 percent, we can say that the respective acquisition rate equals 35 to 40 percent. As the effective net user growth is expected to decrease when approaching the asymptotic maximum of users K, we assume an expected initial acquisition rate of 40 percent. The drift of the respective Brownian motions is assumed to be zero, i.e. the growth rate is assumed to be constant. The combined annual volatility of acquisition and churn rates is assumed to be equal to the volatility of historic annual net growth rates. Computing this value for user growth between 2013 and 2019 results in a quarterly volatility of 5.2%. We can apply the general fact that $\mathrm{Var}(X - Y) = \mathrm{Var}(X) + \mathrm{Var}(Y) - \mathrm{Cov}(X, Y)$. Assuming that the volatilities of a_t and c_t are equal and their correlation coefficient is -0.6, we arrive at an estimation for σ^a and σ^c of around 0.088.

Gross margin: the gross margin is directly observable from the income statement. It is calculated by taking the share of gross profits in total revenues. Average Revenue per User: this can be easily calculated by dividing total (quarterly) revenues by the total number of users. The total number of users over one period is calculated by averaging the number of users at the beginning and end of the regarded period.

Cost of customer acquisition: this metric is simply the periodical marketing expenses divided by the number of newly acquired users. The number of new users is given by the number of users at the beginning of the period times the quarterly acquisition rate of 10%.

Fix costs: this is the sum of all other operating expenses directly observable from Netflix's income statements.

Asymptotic limit of total users until T: estimation of this variable is a little tricky, as it is not directly observable. In Q1 2019 Netflix had about 149 million paid subscriptions. Netflix has been engaged in an extensive internationalization strategy between 2011 and 2017. In 2017, management has announced that Netflix is now available in more than 190 countries around the world. However, it will take some time to penetrate these markets and build regional popularity. The population of households with internet access in these regions amounts around 1,230 million. However, as the number of people with internet access is rising due to global population growth and increasing deployment of internet connections, especially in developing countries, we expect this number to increase by 10% per quarter over the forecast period of 15 years, resulting in a limit of 1,375 million potential users. For simplicity reasons, we assume that, due to the expansion strategy of Netflix during the past years, this number has been increasing by 10% per quarter. Thus, the K for Q4 2018 is 1,250 million, for Q3 2018 1,136 million and so on. The resulting input parameters suggest that over the next 15 years, Netflix will grow with an expected but uncertain acquisition rate of 40% and churn rate of 10% until it reaches the maximum of K users. Despite the uncertainty in growth rates, Netflix's user base can never exceed K.

Coefficient of correlation between acquisition and churn rates: as acquisition rates and churn rates are not separately disclosed, we have to make an assumption about this value. It is intuitive that in case acquisition rates go down, churn rates will go up. This could for instance, be a result of decreasing perceived attractiveness of the product or increasing popularity of competitive products (e.g. Amazon Prime Video). On the other hand, decreasing churn rates suggest high user satisfaction, which will also attract more new users (e.g. Word of Mouth effect). Thus, typically, there is a strong negative correlation between variations in these two metrics. In our simulation, we assume the coefficient of correlation to amount -0.6.

Weighted average cost of capital: the WACC is typically calculated by applying the capital asset pricing model (CAPM). It is the weighted average of a company's cost of equity and cost of debt, while the cost of equity is calculated based on the company's beta. Our research has shown that Netflix's WACC lies between 9% and 11%. Thus, we assume a constant WACC of 10%.

Effective tax rate: Netflix's effective tax rate is subject to strong deviations. However, its average is close to 30%. This number can be found in the respective annual reports.

Terminal growth rate: we assume that the customer lifetime values after T will grow at an annual rate of 2%.

Length of the forecast period: we choose a relatively long time-horizon of 15 years for our forecast. While this explicitly assumes that our metrics follow the presented equations over the next 15 years, the inherent uncertainty increases across time allowing for a large variety of different scenarios.

After estimating all input parameters, we run 100,000 simulations to find Netflix's customer equity at the end of Q1 2019. We compare the resulting customer equity with the spot market capitalization and the CE per share with the spot share price on the first day in the new quarter (i.e. 2019/04/01). Table 3 summarizes the results of the simulation. Figure 2 shows 1,000 example sample paths of user diffusion and the resulting distribution of simulated customer equity.

We receive a customer equity of roughly 164.6 billion USD, which is remarkably close to the respective market capitalization of 160,2 billion USD. Accordingly, the CE per share of 376.91 USD is less than 10 USD higher than the spot share price of 366.96 USD. As no sample path hits zero, the probability of extinction (i.e. the case Netflix's user base drops to zero within the next 15 years) is smaller than 0.001%. Increasing the volatility in the simulation will result in an increasing extinction probability.

Label	Description	Value	Estimation
U_0	User base Q1 2019	148,863,000	Disclosed number of subscriptions
a_0	Annual acquisition rate	40%	Historic annual growth rate of around 30%; assumption that the number of acquisitions is on average 4 times higher than the number of churns
c_0	Annual churn rate	10%	
π	Gross margin	36.5%	Gross profit divided by total revenues
ARPU	Quarterly average revenue per user	$31.38	Total revenues divided by number of users
CAC	Cost of Customer Acquisition per user	$44.28	Marketing & Sales expenses divided by number of new users
F	Quarterly fixed costs	$574,716,000	All other expenses from the income statement (e.g. R&D)
K	Asymptotic maximum of potential users at time T	1.375 billion	Estimation of total market size at time T
ρ	Coefficient of correlation between deviations in acquisition and churn rate	-0.6	Assumption
σ^a	Annual volatility of acquisition rates	8.8%	Calculated from the volatility of historic growth rates
σ^c	Annual volatility of churn rates	8.8%	
μ^a	Expected annual growth of acquisition rates	0%	Assumption
μ^c	Expected annual growth of churn rates	0%	Assumption
r	Company WACC	10%	CAPM calculation
τ	Corporate tax rate	30%	Disclosed by Netflix (annual report)
g	Growth rate of CLVs after T	2%	Assumption
T	Length of forecast period	15 years	Assumption
N	Number of simulations	100,000	Assumption

Table 2: Parametrization of input variables estimated based on Netflix quarterly results Q1 2019

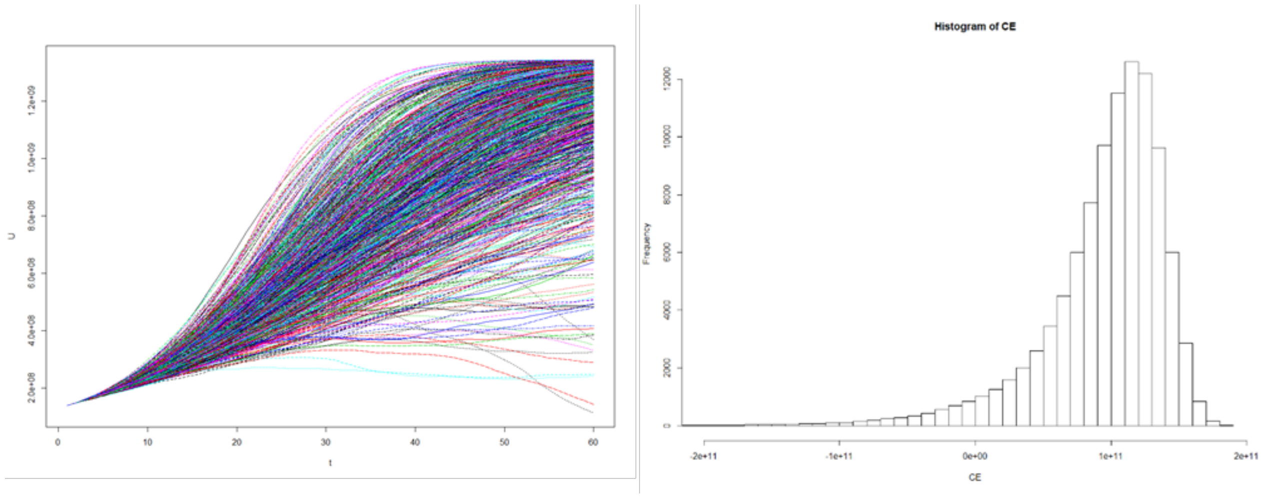

Figure 2: Simulation results – example sample paths and CE distribution

Based on the results, the model seems to generate CEs that are reasonably close to the company's market capitalization. However, in order to check if the model is also suitable to explain historic market capitalizations, we additionally run the same simulation for all historic quarters from Q1 2013 to Q4 2018. The input parameters are recalibrated for each quarter based on the respective quarterly results. Figure 3 shows the simulated CE per share and the spot share price on the first day of each new quarter.

Figures 3 and 4 show that our estimations track Netflix's market capitalization remarkably well. Simulated CE values are within the spread of the share prices during the respective quarter in large parts of the regarded time horizon. In quarters where the difference is high, the model mostly shows CEs that are smaller than the market capitalizations, which could be explained by the model neglecting some of the metrics that are typically included in company valuations, such as changes in working capital, capital expenditures and depreciations.

5 Conclusions

This paper extends existing literature on customer-based company valuation by using a logistic birth-death-rate process including uncertainty about growth rates. We have explained why traditional company valuation techniques have difficulties to justify the large market capitalizations of successful digital companies. We have suggested user-based company valuation techniques as an alternative that is based on user behavior and user growth. We developed a stochastic logistic company valuation model that includes the most important metrics for value-based management of user-based businesses and explained how to estimate the required input parameters. We have then applied the model to estimate the customer equity of Netflix over the last six years. Our results show, that the suggested CE model tracks the market capitalization of Netflix remarkably well. Despite the simplicity of the model, user forecasting and CLV calculation seems to be sufficiently accurate. However, we acknowledge the limitations of our model. The presented model is only suitable for valuing subscription-based businesses. Thus, it assumes a fixed and known revenue stream for every user. Future research could

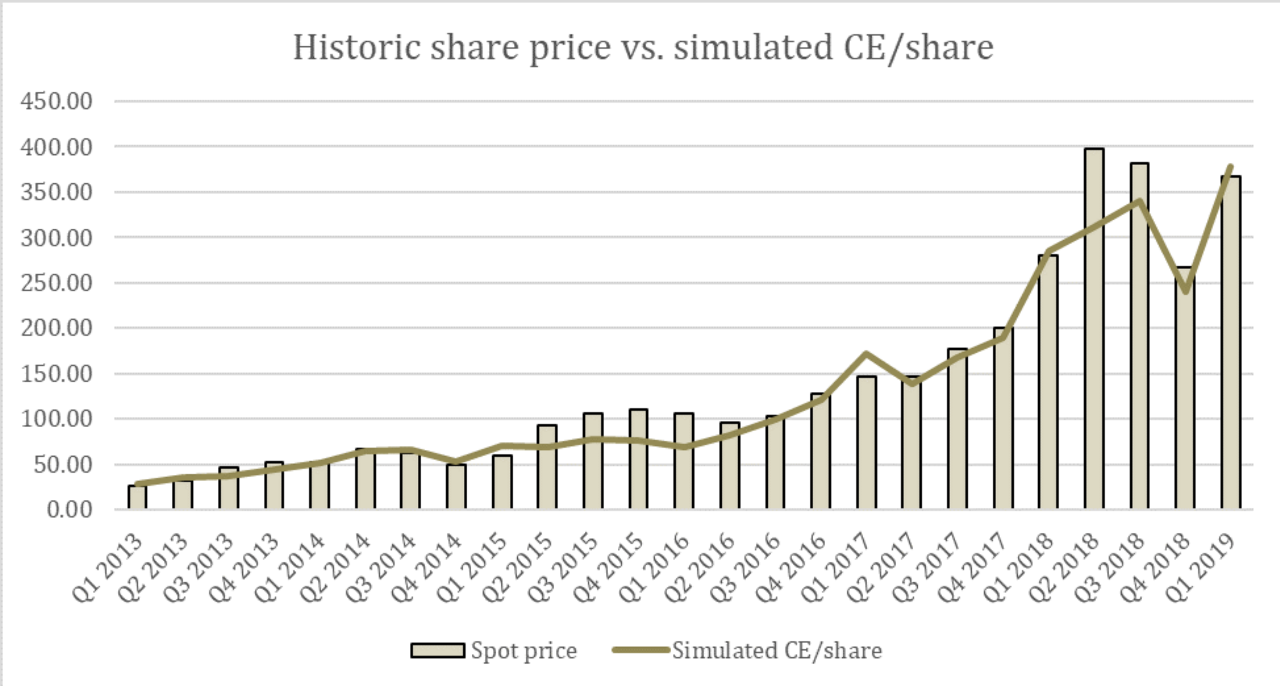

Figure 3: Back testing Q1 2013 – Q1 2019

extend the model to freemium models, for example by modeling two different revenue streams by user types and a conversion rate, which describes the probability of a free user becoming a premium user. The model could further be extended to be applicable to platform businesses by including network effects. It would also be interesting to run sensitivity analysis to identify the most critical value drivers and derive managerial actions based on the findings. The inherent uncertainty would also allow for the valuation of managerial flexibility by analyzing potentially existing real options.

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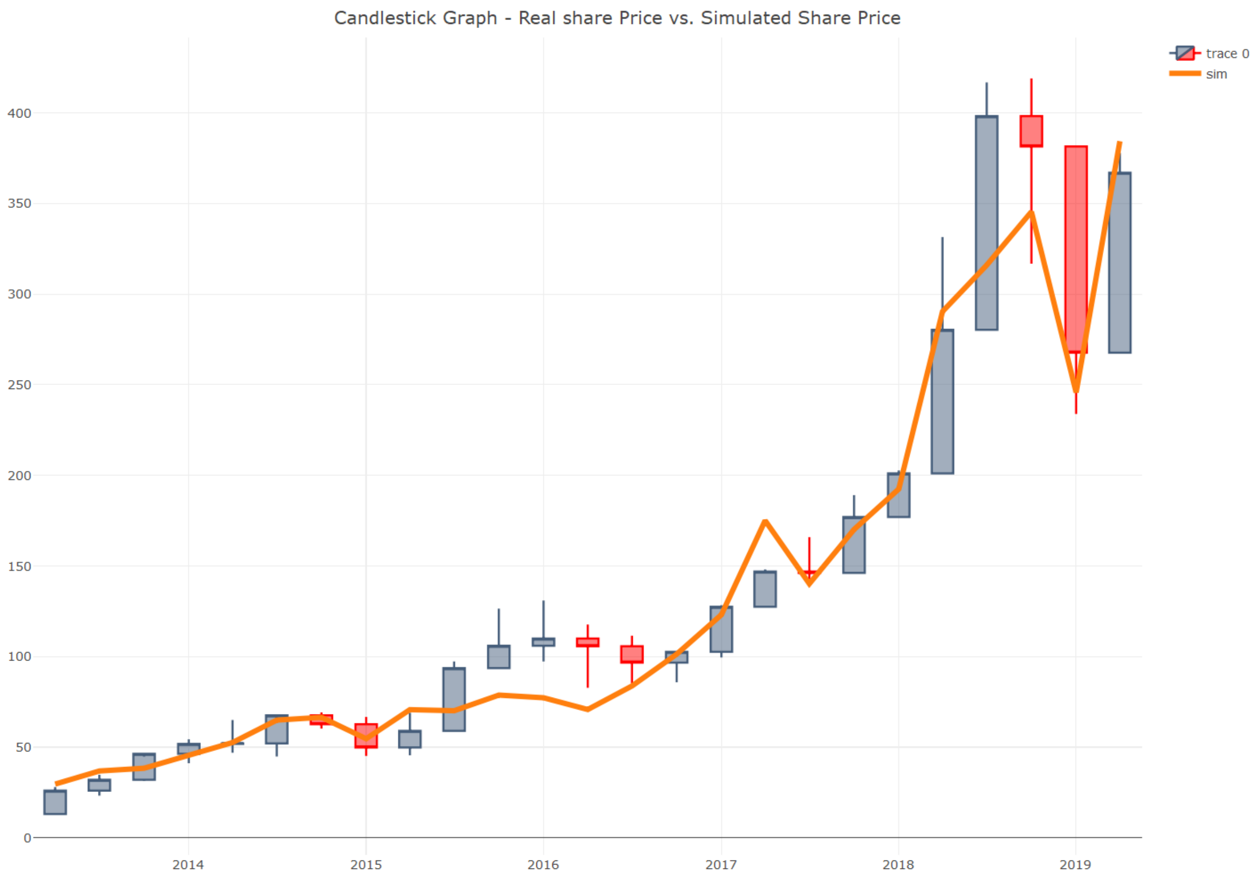

Figure 4: Back testing Q1 2013 – Q1 2019 – Simulation vs. Real High-Low-Open-Close Market Data

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