Research Report

Customer Loyalty Trajectory for B2B Firms: Unveiling Patterns of Retention

CUSTOMER LOYALTY IS A CRITICAL MEASURE FOR SUCCESS, SHOWING IF A FIRM'S PRODUCT IS RECEIVED WELL BY ITS CUSTOMERS. TO UNDERSTAND ITS DEVELOPMENT OVER TIME, TWO FUNDAMENTAL QUESTIONS MUST BE ANSWERED: (I) HOW WILL CURRENT CUSTOMERS' LOYALTY DEVELOP, AND (II) WILL NEW CUSTOMERS' LOYALTY DIFFER FROM CURRENT CUSTOMERS' LOYALTY? THE AUTHORS EMPIRICALLY ANSWER THESE QUESTIONS BASED ON A DATA SET INCLUDING ~500 B2B WEB TECHNOLOGIES WITH JOINTLY ~325 MILLION CUSTOMERS SPANNING OVER 24 YEARS. THEY SHOW THAT LOYALTY HARDLY DEVELOPS AND, IF SO, IT RATHER DECREASES THAN INCREASES. THE LOYALTY OF CURRENT CUSTOMERS RARELY CHANGES AND, IF SO, RATHER INCREASES THAN DECREASES. NEW CUSTOMERS ARE MOST LIKELY LESS LOYAL THAN CURRENT CUSTOMERS. THESE RESULTS SHOW THAT BY FAILING TO ACCOUNT FOR THESE UNDERLYING DEVELOPMENTS, STAKEHOLDERS, IN MOST CASES, DRAW THE WRONG CONCLUSIONS ABOUT PRODUCT VALUE MEASURED VIA CUSTOMER LIFETIME VALUE.

Johannes Roscher
Ali Tamaddoni
Bernd Skiera

Introduction

The success of a firm depends on its customers. The development of the number of customers is therefore highly relevant for managers, investors, and analysts. While firms can often influence the number of newly acquired customers by the size of the marketing spend, observing customer loyalty provides insights into the underlying trajectory (Ellis and Brown, 2017; Ries, 2011; TechCrunch, 2022). Observing customer loyalty across customers acquired at different points in time can, however, lead to the wrong conclusions if its underlying forces are overlooked (McCarthy et al., 2024).

Suppose an investor would, for example, look at the loyalty development of Company A in period 5 in Figure 1. In that case, he/she observes a customer loyalty rate that seems constant at ~80% in the first five periods. However, the observed loyalty can decrease significantly in the following years. Why? The overall loyalty development is driven (I) by an increase in loyalty of current customers and (II) by a decrease in loyalty of new customers compared to current customers. While the contrary development of the two drivers equals out at the beginning of the firm's lifecycle, over time, the decrease in new customers' loyalty outweighs the gain in current customers' loyalty, leading to an overall lower loyalty rate. The contrary loyalty dynamics mislead the stakeholder to an over- or underestimation dependent on the measurement method used for firm success.

A priori, sound reasoning exists for each direction of the loyalty movement. Current customers' loyalty could increase over time due to survival bias, with customers with a lower product fit churning early on and customers with a higher fit remaining (Fader and Hardie, 2007; Gupta and Lehmann, 2005; Kumar and Reinartz, 2018; McCarthy et al., 2024). However, on the contrary, customer saturation could increase with increasing duration of customer affiliation, and the product (which could be a good software or service) becomes less valuable, leading to decreasing customer loyalty (McCarthy et al., 2024).

For new customers' loyalty development, loyalty could increase as the product first must be

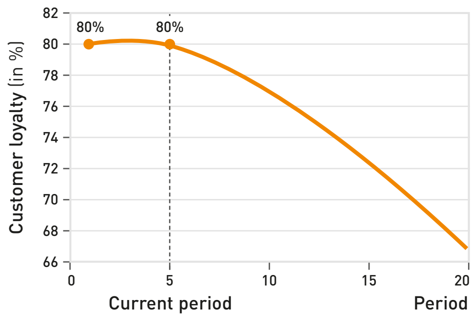

Figure 1: Exemplary Customer Loyalty Development of Company A

established in the market (Prins et al., 2009) before attracting more established customers with higher loyalty. Otherwise, loyalty could decrease as the customers with the highest fit become customers early on, with later acquired customers being less loyal (Eisenmann, 2021).

So, insights into which direction the loyalty of current and new customers develops help investors, analysts, and managers to better evaluate future firm performance. Therefore, we aim to answer the following research questions:

1. How will current customers' loyalty develop over time?
2. How will new customers' loyalty differ from current customers' loyalty?
3. Which drivers impact loyalty development? (e.g., technology types, customer growth, location of technology's headquarters)
4. How will the change in current and new customers' loyalty impact overall loyalty?

Research Approach

To answer these questions, we construct period-cohort tables, whereby we group customers into cohorts based on the year of their first purchase. They are then tracked along their age (i.e., the time they have been customers), showing the number of customers who remained active in the next year out of the initially acquired customers of the cohort. We convert these tables to year-to-year retention tables, showing what proportion of customers of a cohort in a period remained active in the next period (note, the value in each cell is between 0 if all customers churn, and 1 if all customers stay).

The development of retention rates along the table is equal to the development of current customers' loyalty (hereafter the age effect – corresponding to research question 1), while the difference in retention rate between the cohorts is equal to the difference in new customers' loyalty compared to current customers' loyalty (hereafter the cohort effect – corresponding to research question 2).

Data Set

To empirically answer our research questions, we assemble a B2B data set including 689 web technologies, hereafter referred to as technologies each treated as an independent entity, out of which we keep (after several data cleaning steps) 497 technologies with more than 325 million customers. The data set comprises eight technology types (e.g., web hosting and infrastructure, advertising and marketing, content management and development) and spans 24 years (2000 to 2023).

Looking at the average churn rates across technologies, we see that after 3 years, on average, 55% of customers churned. Looking at average customer loyalty by technology type, we see only small differences between categories: All average loyalty rates are between 73% and 75%, apart from Email Hosting at 90% and Media and Content Delivery at 64%. In addition, we can observe a difference between the average loyalty rate of technologies in the US (76%) and other geographic areas (80%), which is significant with a p-value of 0.04% based on the Mann-Whitney U test.

Results

To assess the direction of the age and cohort effect across our full sample, we run individual regressions for each technology, summarizing the direction of effects in Figure 2. It shows the number of significantly positive, neutral, and significantly negative coefficients for the age and cohort variable of the individual models across our sample. First, looking at the age and cohort effect separately, we see that 279 of the 497 technologies have a neutral, i.e., no age effect. Out of the remaining 218 technologies, 162 show a positive and 56 a negative age effect.

We conclude that the age effect is primarily neutral but more likely positive than negative. The cohort effect, on the other hand, is negative for 260 technologies and neutral for 203 technologies. Looking at the interaction of the effects, we see that if the cohort effect is positive, the age effect is also often positive. When the cohort effect is neutral, the age effect tends to be neutral or positive. In contrast, if the cohort effect is negative, the age effect is reasonably balanced between positive and negative; however, it is mostly neutral.

To analyze the impact of potential drivers on the age and cohort effect, we run three separate regressions with all drivers as independent variables of each regression and the age, cohort, and constant of the previously derived age-cohort OLS regression models as the dependent variables. As drivers, we investigate (I) the year of technology establishment, (II) the technology origin country, (III) the growth of the company, (IV) the age of customers, and (V) the technology type.

We show that the year a technology has been established, the technology's origin country, and the average age of cohorts' customers only drive overall loyalty. Technologies established later have lower loyalty, technologies with their firms' headquarters in the US have lower loyalty, and technologies with a higher average age of

N = 497

		Age effect			
		Positive	Neutral	Negative	Total
Cohort effect	Positive	27	6	1	34
	Neutral	81	115	7	203
	Negative	54	158	48	260
	Total	162	279	56	497

Number of observations: Low High

Figure 2: Overview of the Direction of Age and Cohort Effect (Significance Level >5% and Positive/Negative Coefficient >0.3% Required for Non-neutral Classification)

N = 497

		Cohort effect	
	Technologies	Not considered	Considered
Age effect	Not considered	*Constant loyalty assumption*	322 *(65%)* 175 *(35%)*
	Considered	200 *(40%)* 297 *(60%)*	188 *(38%)* 309 *(62%)*

Limited effect (+/-10% deviation from constant loyalty development)

Major effect (> +/-10% deviation from constant loyalty development)

(x%) Share of technologies of total

Figure 3: Overview of the Number of Technologies by Deviation from CLV, Including Age and Cohort Effects (Assuming Time Shift for Cohort Effect of 5 Periods, Maximum Retention Rate of 99%, and a Discount Rate of 10%)

customers (i.e., how long the customer existed before being acquired) have a higher loyalty. The type of technology, however, influences the cohort effect and the overall loyalty, with the direction and significance of the effect depending on the specific technology type. The growth of the company has no significant impact on the age effect, cohort effect, or overall loyalty level. The age effect is not significantly impacted by any of the investigated drivers overall.

To see whether the age or cohort effect has a stronger impact on the overall retention rate across technologies, we run an OLS regression with the overall retention development analysis coefficients as dependent and the age and cohort effect coefficients as independent variables. We see that the age and cohort coefficients are both highly significant, with the cohort coefficient having a higher z-value (15.686 vis-à-vis 4.099) and a higher coefficient (0.704 vis-à-vis 0.1805). We conclude that the cohort effect is more relevant for the overall retention development than the age effect in our sample. This conclusion corresponds with our observation of a higher share of technologies with a negative overall loyalty trend, driven by the negative cohort effect.

Managerial Implications

We show that the age effect tends to be neutral or positive, and the cohort effect tends to be neutral or negative, with the overall loyalty being more likely to develop negatively than positively but keeping a neutral development in most cases. The question, therefore, is: Do stakeholders even need to care about the effects or do the opposing age and cohort effects counterbalance each other?

To investigate this question, we calculate four exemplary customer lifetime values (CLVs) for each technology, by (I) not including any age or cohort effects, (II) including only the respective age effect, (III) including only the respective cohort effect, and (IV) including both effects. We assume the base loyalty level, the age, and the cohort effect to correspond to the intercept, the age, and the cohort coefficient of our initial age-cohort OLS regression per technology. After calculating the four CLVs per technology, we calculate the differences for the CLVs, including only the age effect, the cohort effect, and the age and cohort effect compared to the CLV, excluding both effects.

In Figure 3, we show, dependent on the included effects, the share of technologies for which the deviation in CLV compared to the constant loyalty CLV is larger than 10%. Accordingly, if only considering the age effect, we see that the CLV deviates for 60% of technologies by more than 10%. The standalone cohort effect leads to a deviation of >10% for 35% of technologies. If both effects are included, we see that the CLV is significantly impacted for 62% of technologies. We observe that 33% of technologies deviate by ±10-25% compared to a constant loyalty assumption, and 29% deviate by more than 25%. In addition, we see an equal distribution in the number of technologies between technologies deviating by more than +10% (32%) and by deviating more than -10% (31%).

We conclude that the age and cohort effect significantly impact the CLV calculation in most cases, highlighting the need for stakeholders to consider them in their assessments. Startup investors, in particular, should request customer loyalty data not only on an overall level but also cohort-by-cohort to predict future development. As shown in the initial example of this paper, a contrary age and cohort effect can, jointly with customer growth, lead to the wrong conclusions, e.g., by assuming a firm has constant customer loyalty when, in reality, the customers with the highest product-fit have already been acquired, leading subsequently to customers with lower loyalty. We, therefore, argue that outside stakeholders should urge firms to publish their customer loyalty developments on a cohort level, providing insights into the underlying dynamics of the firm trajectory.

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