Product Returns and Lifetime Value in Subscription Retailing

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Abstract

Prior research has studied customer lifetime value (CLV) and product returns in isolation, but their dynamic relationship — particularly in subscription retail contexts where returns may signal customer engagement — remains underexplored. To fill this gap, we estimate a hidden Markov model (HMM) on transaction data from 28,923 subscribers of an online apparel retailer. We link expected revenues, churn probabilities, and CLV to observed return rates. Our findings reveal two insights: (1) Returns and CLV have a non-monotonic relationship as zero-return customers exhibit 25-40% lower CLV than some selective returners, suggesting returns reflect engagement, not just dissatisfaction. (2) Customer tenure moderates this effect, with return rates' impact on CLV varying up to 30% between the first and second subscription months. This research contributes to theory and practice by establishing returns as a behavioral CLV indicator and offering actionable strategies for retention optimization.

Keywords: hidden Markov model, product returns, customer lifetime value

Track: Methods, Modelling & Marketing Analytics

1 Background and Motivation

Product returns have recently emerged as a critical challenge with major implications for firms, particularly in the rapidly rising e-commerce sector where customers expect no-hassle return policies and processes. As noted in the 2023 Consumer Returns in the Retail Industry survey published by the NRF,[1] returns amounted to a staggering 14.5 percent of retail sales in the United States, resulting in an estimated $743 Billion in lost sales for retailers. Importantly, the manner in which returns are handled and resolved can either reinforce brand loyalty or exacerbate dissatisfaction, thereby shaping future purchasing decisions and brand perception (El Kihal & Shehu, 2022). Thus, product returns may be an important antecedent of customer churn and CLV.

According to common wisdom, higher purchase levels are a strong predictor of longer customer lifetime. However, the literature is ripe with exceptions to this rule (Reinartz & Kumar, 2000; Seiders et al., 2005). In the contractual setting, the literature jointly modeling these two main determinants of CLV tends to show a monotonic relationship between consumption and customer lifetime (Ascarza & Hardie, 2013; Donkers et al., 2007). However, Borle et al. (2008) find that, among customers of a subcription-based direct marketing company, longer interpurchase times are associated with both larger transaction amounts and a greater risk of customer churn.

Around the turn of the millenium, the setting of Borle et al. (2008), wherein marketers only learn about purchases — and the prolonged lifetime of the buyer — once a transaction happened, was typical for "catalog marketers." In contrast, in modern-day subscription retail, consumers often receive an assortment of products from the firm, choose some items to retain (and pay for), and return the rest of the items.

We aim to illuminate the dynamics between product return behavior and CLV in the subscription retail industry. To this end, we analyze data on the purchases and product returns of 28,923 customers of an online subscription retailer. We model the dynamics of subscribers' purchases and their decision to pause or cancel the service using a hidden

[1] https://nrf.com/research/2023-consumer-returns-retail-industry

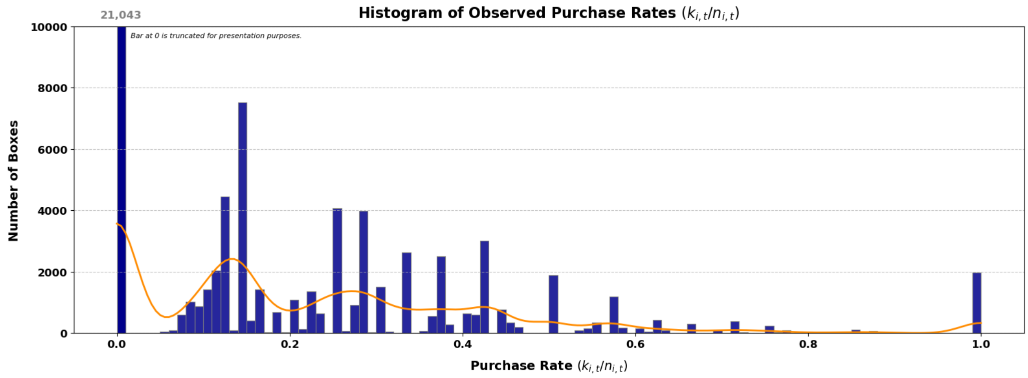

Figure 1: Purchase rates $k_{i,t}/n_{i,t}$ (where $k_{i,t}$ items out of a box of $n_{i,t}$ were purchased).

Markov model (HMM, Netzer et al., 2008). We find a non-monotonic relationship between purchase rates and churn probabilities. In addition, we demonstrate that, while CLV tends to increase with purchase rates, there is a surprising exception to this rule: subscribers who do not engage in product returns at all are not the most valuable members of the retailer's customer base. We expect that these insights will make an important contribution to both the academic literature and retail practice.

2 Data

Our data come from a U.S. online apparel retailer that follows a subscription-based business model. For a monthly fee, customers receive a personalized *box* of clothing items curated by a stylist, and can decide which subset of items in the box to return at no cost, and pay only for the retained items. The total price of the purchased goods is offset by the subscription fee. However, even if customers purchase goods of a lower total value or even return all items, they need to pay the subscription fee. Subscribers may terminate the service at any point after the first month. In addition, they also may decide to pause the service for (referred to as "skip" hereinafter) up to two months — after the pause, the service automatically continues with the next monthly box.

The data contain the demographics and subscription activity of $I = 28,923$ unique customers who subscribed to the service during the first 31 months of the service (06/2015-12/2017). We observe all purchase interactions (contents of boxes shipped, and items purchased and returned) up to April 2018, at which point 3,588 customers in the observed cohort had not yet terminated their subscription.

We observe a total of 78,840 boxes shipped. For each box, we observe the detailed description and retail price (M=$86.91, SD=$44.52) of each product in the box, as well as the customer's purchase decision for each item. The average box contains 8.92 items, of which only 1.99 items are purchased (and 6.93 returned to the retailer). Figure **1** shows the distribution of purchase rates across all boxes shipped.

We can only infer (but not directly observe) "skip" and "churn" decisions based on sequences of months without a box shipped by the retailer. For sequences containing at least three months without boxes shipped, we infer that the customer churned in the month after receiving their last box. For sequences of up to two months without boxes shipped, we infer that the customer "skipped" the applicable number of months if the sequence is followed by the receipt of another box from the retailer. For up to two months without boxes right before the end of the observation window, we consider both the possibility of a "skip" and a "churn" decision (and account for this in our model).

3 Model

To address the relationship between product returns, churn, and customer lifetime value, we treat items in each box as interchangeable, and model the *number of items* purchased from each box. This allows us to express CLV in terms of the average price and gross margin on an item, and the costs of shipping boxes and processing product returns.

We assume that both customers' purchase decisions as well as their decision to skip or terminate the service reflect some latent variable *Engagement*. Following Ascarza and Hardie (2013), we assume this variable being discrete and evolveing in a stochastic manner. We capture customer heterogeneity simply by not assuming a monotonic relationship between purchase, skip, and churn behaviors. Instead, we assume a combination of "value states" (to describe behavior in months when a box was sent to customer), "skip states" (one each for the first and the second month skipped, respectively, to capture customers re-engagement with the subscription service), and an absorbing "churn state" that is the terminal state for each customer journey.

Our model captures two main processes: (i) the evolution of customers' engagement with the service, and (ii) the monthly purchase decision regarding how many items to buy from the box received. To jointly model these two processes, we assume that the latent variable *Engagement* represents customers' decision to pause or terminate their subscription and their predisposition to purchase items from the product assortment received from the retailer each month. To capture changes in customer behavior, we allow *Engagement* to vary stochastically from month to month and we model its evolution as a hidden Markov process (Ascarza & Hardie, 2013; Netzer et al., 2008).

3.1 Evolution of Customer Engagement

Let $t \in \{1, 2, \ldots\}$ denote the months of a customer's subscription for customers $i \in \{1, 2, \ldots, I\}$. The K states, $1, 2, \ldots, K$, represent the possible engagement states that each customer could occupy at any point along their journey with the retailer.[2] Of these states, state K is the absorbing churn state, while $K-2$ and $K-1$ are associated with the first and — if applicable — second months of paused subscriptions, respectively. We assume that $S_{i,t}$, the state of customer i in the t^{th} month of their subscription to the service, evolves over time following a Markov process with transition matrix $\mathbf{A} = (a_{j,k})$, meaning that $\Pr(S_{i,t} = k \mid S_{i,t-1} = j) = a_{j,k}$. As we can only label states reflecting churn and skip behaviors ex-post, we further constrain $\mathbf{A}$ such that

$$a_{j,K-1} = 0 \text{ for } j \neq K-2, \tag{1}$$

$$a_{j,K-2} = 0 \text{ for } j \in \{K-2, K-1\}, \tag{2}$$

$$a_{j,K} = 0 \text{ for } j \in \{K-2, K-1\}, \text{ and} \tag{3}$$

$$a_{K,j} = \begin{cases} 0 & \text{if } j < K \\ 1 & \text{if } j = K \end{cases}. \tag{4}$$

Finally, for newly-acquired customers, we assume that $\Pr(S_{i,1} = k) = \pi_k$ for

[2] Consistent with past research on HMMs, the latent state space is common across all subscribers.

$k \in \{1, 2, \ldots, K\}$, with $\pi_k = 0$ for $k > K-3$. Let $\tilde{S}_i = [S_{i,1}, S_{i,2}, \ldots, S_{i,T_i}]$ denote the (unobserved) sequence of states to which customer i belongs during the observation window, with realization $\tilde{s}_i = [s_{i,1}, s_{i,2}, \ldots, s_{i,T_i}]$. Their "engagement" likelihood is then

$$f^{\text{engagement}}(\tilde{S}_i = \tilde{s}_i \mid \mathbf{A}, \boldsymbol{\pi}) = \pi_{s_{i,1}} \cdot \prod_{t=2}^{T_i} a_{s_{i,t-1}, s_{i,t}}.$$

3.2 The State-Dependent Purchase Process

We assume that subscribers' purchase choices reflect the *Engagement* variable, such that for $1 \leq k \leq K-3$ — the *active states* — subscribers' purchase decisions in state k follow a Binomial distribution with a state-specific parameter p_k. Specifically, when the retailer sends a box of n assorted items to a subscriber in state k, then the probability that they purchase m of those items follows $B(n, p_k)$, i.e., a Binomial distribution with parameter p_k, where p_k is a state-dependent parameter that is common for all subscribers in state k and constant across different time periods.

Since for states $K-2 \leq k \leq K$, we know with certainty that the retailer did not send a box (i.e., $n = 0$), we define $p_k = 0$ for $k \in \{K-2, K-1, K\}$, and thus the purchase likelihood for any given period generalizes to

$$\Pr(m \mid S_i = k, n, \mathbf{p}) = \begin{cases} B(n, p_k) & \text{if } k \leq K-3 \text{ or } n = 0, \text{ and} \\ 0 & \text{otherwise} \end{cases}.$$

We do not assume that the likelihood of churn and/or skip behaviors in state k are monotonically linked to p_k. However, since Figure **1** shows a substantial probability that consumers purchase every item in the box shipped to them, for each tested value of K, we estimate both a model where we constrain $p_{K-3} = 1$, as well as a model with no constraint on the p_{K-3} parameter value.

For each customer i, we have a total of T_i observations. Let $\mathbf{n}_i = (n_{i,t})$ be the vector containing the number of products sent to customer i in each period (with $n_{i,t} = 0$ when i's subscription is not active, i.e., when $S_{i,t} > K-3$), and $\mathbf{m}_i = (m_{i,t})$ be the number of items purchased by customer i in the corresponding periods. The customer's "purchase" likelihood function, using the definition of $\tilde{S}_i$ from the previous section, is then

$$f^{\text{purchase}}(\mathbf{m}_i \mid \tilde{S}_i, \mathbf{n}_i, \mathbf{p}) = \prod_{t=1}^{T_i} \Pr(m_{i,t} \mid S_{i,t}, n_{i,t}, \mathbf{p}).$$

3.3 Overall Model Likelihood

Let Γ_i denote all possible commitment state paths of customer i. Then the overall likelihood function for each customer is

$$L_i(\mathbf{m}_i, \mathbf{n}_i, \mathbf{A}, \boldsymbol{\pi}, \mathbf{p}) = \sum_{\tilde{S}_i \in \Gamma_i} f^{\text{purchase}}(\mathbf{m}_i \mid \tilde{S}_i, \mathbf{n}_i, \mathbf{p}) \cdot f^{\text{engagement}}(\tilde{S}_i \mid \mathbf{A}, \boldsymbol{\pi}),$$

where $f^{\text{engagement}}(\tilde{S}_i \mid \mathbf{A}, \boldsymbol{\pi})$ is the likelihood of the unobserved state sequence (*path*) $\tilde{S}_i$. Note that our definitions above render impossible paths to occur with zero likelihood. In contrast, right-censored sequences of one or two months without a box shipped by the retailer may correspond to either a pause in (states $K-2$ and, if applicable, $K-1$) or an overall termination (state K) of the customer's subscription. Accordingly, for the months in question, our model accounts for both possibilities not to bias the parameters of the transition matrix. The overall likelihood function is then simply

$$L(\text{data}, \mathbf{A}, \boldsymbol{\pi}, \mathbf{p}) = \prod_{i=1}^{I} L_i(\mathbf{m}_i, \mathbf{n}_i, \mathbf{A}, \boldsymbol{\pi}, \mathbf{p}),$$

where "data" refers to all I observed customer journeys with the retailer.

4 Results

4.1 Model Selection

To identify the optimal number of hidden states, for each $5 \leq K \leq 12$, we estimated one model with no constraint on p_{K-3}, and one assuming that $p_{K-3} = 1$, respectively. Hereinafter, we refer to the constrained and unconstrained models by $X = 1$ and $X = 0$, respectively, and label state $K-3$ as the value state of "extremely high engagement."

For each model, there are $K^2 - K - 8 - X$ free parameters to estimate. We chose the starting values $p_k = 1/(K-2-k)$ for the state-specific purchase rates, $\pi_k = 1/(K-3)$ for the initial probability of each state, $a_{j,k} = 1/(K-1)$ for $j \leq K-3, k \neq K-1$ for the transaction probabilities out of value states, $a_{j,K} = 1/(K-2)$ for $j = K-2, k \notin \{K-2, K\}$, and $a_{j,k} = 1/(K-3)$ for $j = K-1, k \leq K-3$ for the two "skip" states. The rest of the entries in $\mathbf{A}$ were constrained to 0, save for $a_{K,K}$, constrained to 1, as explained in section 3.1.

After estimating each model using the Baum-Welch algorithm, we retained the $K = 11, X = 1$ model (with seven unconstrained value states plus the one with no returns) based on its minimal BIC score.

4.2 Dynamics of Consumer Behavior

Of the $K = 11$ hidden states of the retained model we refer to states 1-7 as "V1"-"V7," to state 8 as "X," to states 9-10 as "S1"-"S2," and state 11 as "C," respectively. Figure **2** shows the estimates for the transition matrix $\mathbf{A}$, and Table **1** reports the initial probabilities of, as well as the purchase rates associated with each value state. Together, these figures indicate a decreasing trend in purchase rates over time. [3] However, while the weighted (by the initial state probabilities $\boldsymbol{\pi}$) correlation of purchase rates p_k and churn probability $a_{k,K}$ for the eight value states is -.64, indicating that purchase rates

[3] We note that the purchase rates are not monotonically increasing with the state index for $1 \leq k \leq 8$ as state V4 has a purchase rate above that of V5 and V6.

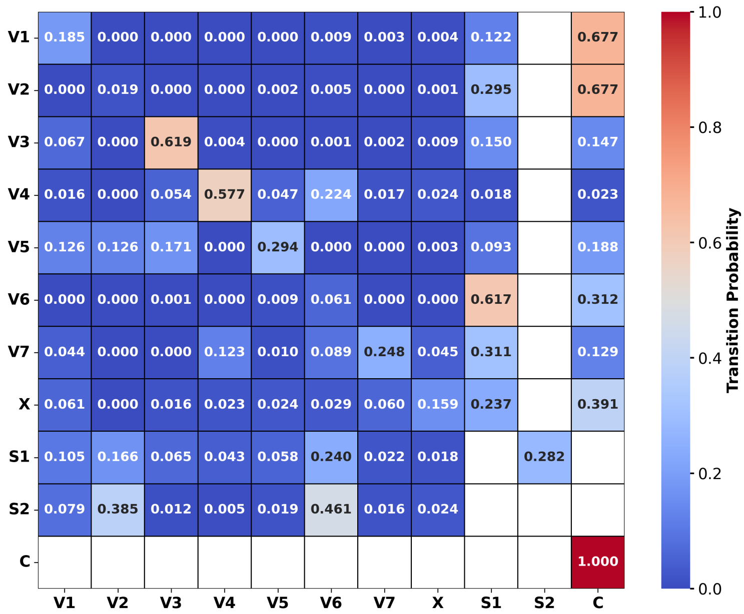

Figure 2: Transition matrix of the selected model (K=11, X=1). V1-V7 and X are the eight value states, S1-S2 are the states corresponding to the first and, if applicable, second month of pauses in customers' subscription, and state C is the absorbing churn state. Cells constrained to 0 are shown as white squares.

are generally negatively related to churn, there are several state pairs wherein one state has a higher estimate on both measures, suggesting that some customers purchasing more in the current month may have an overall lower value to the retailer due to their shorter expected lifetime.

Table 1: Initial probabilities (π_k) and purchase rates (p_k) for the value states ($k = 1, 2, \ldots 8$, denoted as V1, ..., V7, X) in the K=11, X=1 model

State	**V1**	**V2**	**V3**	**V4**	**V5**	**V6**	**V7**	**X**
Initial Probability	0.364	0.026	0.000	0.066	0.243	0.225	0.050	0.026
Purchase Rate	0.042	0.093	0.150	0.329	0.229	0.302	0.585	$1^{\dagger}$

† The parameter p_8 was constrained to 1 in the selected model.

4.3 Product Returns and Customer Lifetime Value

To assess CLV, we make the assumptions shown in Table **2** regarding the revenues and costs of the subscription retailer. [4] Let $\boldsymbol{\phi} = (\phi_k)$ and $\boldsymbol{\Lambda} = (\Lambda_k)$ denote the K-dimensional column vectors containing the expected profit contribution of a customer in the current period and the CLV in each state k, respectively. (Note that $\phi_k = 0$ for $k \geq 9$). For easier exposition, we assume that the company is expected to send a box of $n_e = 9$ items. To account for the possibility of cherry-picking, we assume that $P(m)$

[4]Our assumptions are based on, e.g., https://www.frbdiscountwindow.org/pages/discount-rates/historical-discount-rates, and https://www.usps.com/. As the retailer did not use markdowns, we assume a gross margin above the industry average reported in https://csimarket.com/Industry/industry_Profitability_Ratios.php?ind=401. To simplify, we ignore customer acquisition cost.

Table 2: Parameters and Assumed Values for the CLV Model

Parameter	Assumed Value	Description
M_g	0.65	Gross margin of retailer
Cm	\$15	Cost of shipping a box to a customer
Cr	\$1	Fixed cost of processing a returned box
Ci	\$7.50	Cost of processing a returned item (restocking)
F	\$29.95	Monthly subscription fee
r	0.0025	Monthly discount rate (3% annually)

equals the average price of items across transactions where m items were purchased out of a box of n_e items (see Table **3**), and $C_v(z) = (1 - M_g) \cdot P(z)$, Thus,

$$\begin{aligned}
\phi_8 &= P(n_e) \cdot n_e - C_v(n_e) \cdot n_e - C_m, \text{ and} \\
\phi_k &= \Pr[P_k = n_e] \cdot \{P(n_e) \cdot n_e - C_v(n_e) \cdot n_e - C_m\} + \\
&\quad \sum_{m=0}^{n_e-1} \Pr[P_k = m] \cdot \{\max(P(m) \cdot m, F) - C_v(m) \cdot m - C_m - C_r - C_i \cdot (n_e - m)\}
\end{aligned}$$

for $1 \le k \le 7$, where $\Pr[P_k = m] = \binom{n_e}{m} \cdot p_k^m \cdot (1 - p_k)^{n_e - m}$ for P_k, the number of items purchased in the given period.

Table 3: Average price per purchased item, by the number of items purchased out of a box of $n = 9$ products shipped by the retailer.

Items purchased	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Avg. price (USD)	50.93	66.89	66.06	71.06	76.31	79.59	79.95	84.05	81.48

The CLV for each state k obtains as $\Lambda_k = \phi_k + \sum_{j=1}^{K} a_{k,j} \cdot \Lambda_j / (1 + r)$, resulting in the values in Table **4**. Thus, the CLV of a *new customer* is $\underset{t=1}{\mathrm{E}}[\mathrm{CLV}] = \boldsymbol{\pi\Lambda} = \$46.64$.

Table 4: Lifetime value of customers arriving in each hidden value state of the selected model (K=11, X=1). The CLV of 0 in state 11 (C) is omitted for brevity.

State	**V1**	**V2**	**V3**	**V4**	**V5**	**V6**	**V7**	**X**	**S1**	**S2**
CLV	-88.23	-43.91	-50.59	259.40	20.54	93.73	389.90	656.25	47.23	42.32

To assess how the remaining CLV depends on a customer's last observed purchase rate, we assume that they last received a box of $n_t = n_e = 9$ items. As the probability of being in a specific hidden state is not fully revealed by the observed purchase rate, we also take the observed subscriber's tenure (t months) with the firm as input.

Let $\mathbf{V}(m) = \mathrm{diag}(v_1(m), v_2(m), \ldots, v_K(m))$ be a $K \times K$-dimensional diagonal matrix where the elements represent the conditional probability of purchasing m items given the state of the customer, i.e.,

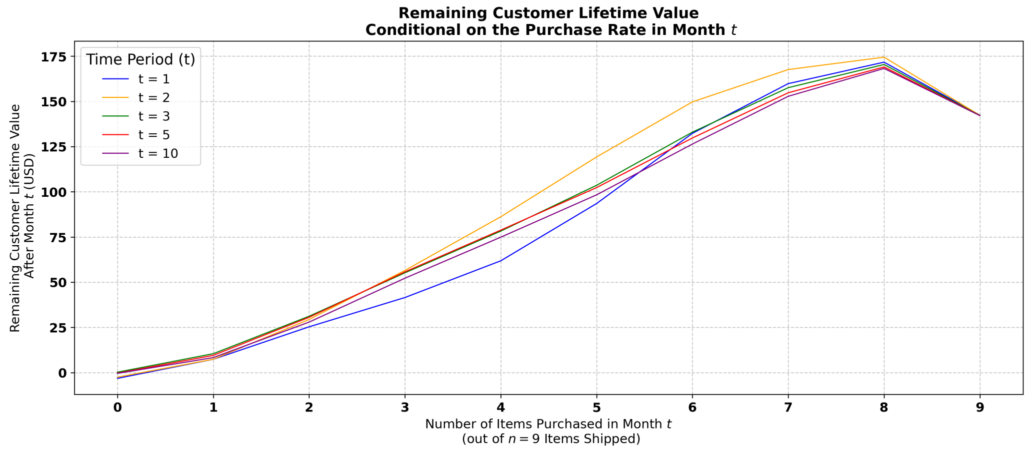

Figure 3: Residual CLV by (1) the last observed purchase rate (m_t out of $n_t = 9$ items bought), and (2) the tenure of the customer (after t months of their subscription).

$$v_i(m) = \Pr(m \,|\, i, n, \mathbf{p}) = \begin{cases} B(n, p_i) & \text{if } i \leq K - 3 = 8 \text{ or } n = 0, \text{ and} \\ 0 & \text{otherwise} \end{cases}.$$

Assuming that the subscriber purchased m_t of the n_t shipped items, their *residual* CLV (not including the current transaction) depends on the posterior distribution of their hidden state, multiplied by the long-term component of their lifetime value according to the transition matrix $\mathbf{A}$. Putting it together gives

$$\mathrm{E}\left[\mathrm{CLV} \mid m_t, t\right] = \boldsymbol{\pi}\mathbf{A}^{t-1}\mathbf{V}(m_t)\,(\boldsymbol{\Lambda} - \boldsymbol{\phi})\,/\sum_{i=1}^{K} v_i(m_t),$$

where $K = 11$ is the number of hidden states in the selected model.

For each specific time period t, the result of this exercise is a mapping function of the domain of the number of items kept ($m_t \in \{0, 1, \ldots, n_t\}$) onto CLV. Figure **3** shows this function for a few key values of t. Notably, while higher purchase rates correspond to higher residual CLV all the way up to $m_t = 8$ out of $n_t = 9$ items purchased, the residual CLV of a customer purchasing all the items shipped to them is lower than that of customers purchasing only $m_t = 7$ or 8 out of $n_t = 9$ items, no matter the tenure of the customer. We speculate that the drop at $m_t = 9$ items purchased from a box of $n_t = 9$ items corresponds to the mechanism accounted for by the hidden state of "extremely high engagement." While a higher number of items purchased may generally indicate a better fit of the shipped products, leading to greater customer satisfaction, customers purchasing every item in a given box may do so due to other reasons, such as aiming to avoid investing their time in assessing the fit of each shipped product, and/or in preparing the return shipment to the retailer. While these customers generate more profit for the firm in the month when they pay for everything in the box, they are also much more likely to pause or cancel their subscription than customers in, e.g., the V4 or

V5 states (cf. Figure **2**), which ultimately lowers their residual CLV relative to customers who buy many but not all items received from the retailer.

In addition, Figure **3** also reveals how the conditional CLV of a customer purchasing a certain number of items depends on the length of the tenure of the customer. The most notable swing in CLV is observed from $t = 1$ to $t = 2$ — to the extent that a customer who purchased 4 out of 9 items at $t = 2$ is more valuable than a customer who purchased 5 out of 9 items at $t = 1$, despite each conditional CLV function (for constant t) increasing, around those purchase rates, by over $30 per additional item kept.

5 Conclusion

Our findings make several important contributions. For academic research, this work represents the first systematic examination of how product return rates relate to customer lifetime value in subscription retail, establishing returns as a key behavioral indicator rather than merely an operational concern. For practitioners, our results challenge the common assumption that minimizing returns automatically maximizes customer value. Instead, they suggest that moderate return rates may signal healthy customer engagement and that extremely low return rates might paradoxically indicate a higher risk of churn. These findings emphasize the strategic importance of managing product returns not merely as an operational cost but as a predictive signal of customer value. Retailers can harness this knowledge to refine personalized marketing, optimize inventory, and tailor return policies to foster loyalty among high-value customers.

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