Time Allocation in Entrepreneurial Selling: Impact of Consumer Peer Learning and Incumbent Reaction

***Index Terms*—**Entrepreneurial selling, technology entrepreneurship, game theory, time allocation.

***Abstract*—**How should technology entrepreneurs allocate their time to potential customers? Considering two important dynamics that influence consumers' purchase decisions regarding new technology products, namely, consumer peer learning and incumbent reaction, we study the tactical-level time allocation decision with a simple game-theoretic model. We offer an economic rationale for the entrepreneur's optimal time allocation for different levels of consumer peer learning and incumbent reaction as well as different revenue distributions between the buyers, and we discuss theoretical and practical implications for technology entrepreneurship.

I. INTRODUCTION

New technology startups have surged in recent decades. Such startups often develop new, superior technology-based products capable of replacing the products of established firms that operate in similar domains. For these technology startups, it is vital to achieve success in the initial sales in the early stages of market entry; this helps the cash-constrained technology entrepreneur not only to survive (i.e., to attain a positive cash flow), but also to establish the necessary reputation for attracting the additional funding that is needed to grow. Indeed, one of the most common reasons for new venture failure, according to existing research, is the inability to effectively bring products to potential consumers [1].

Unsurprisingly, in a recent survey on new ventures, *selling* was identified by early-stage angel and venture capital investors as one of the three most critical business operations that entrepreneurs were least competent in executing [2]. Indeed, despite their technological expertise [3], many innovators have little experience in selling their products [2, 4] and are thus led to ask: "I have a great product, now how to sell it?" [5].

One of the key components of a new venture's selling activity is the entrepreneur's offering a vast number of potential customers a personal explanation of the benefits of its new product relative to existing ones [6]. In observational studies, startup entrepreneurs were often found "drafting their product leaflet and acquiring customers with numerous calls, emails, and sales pitches" [7]. This selling process presents a challenge for many technology entrepreneurs because of the combination of shortages they face in *resources*, *reputation*, and *routine* [8].

First, entrepreneurs lack sales resources. In the early stages of selling, typically the entrepreneur is the only person who is knowledgeable (and passionate) enough about the new product to successfully engage potential customers [9], so it is difficult to outsource this activity. The greater the number of potential customers an entrepreneur can personally engage with, the higher the expected sales. However, entrepreneurs cannot engage with all potential customers, and investing more time in one client necessarily means spending less time with another. Thus, the entrepreneur's time is a critical resource for selling, and its shortage can significantly threaten a product's sales.

Second, entrepreneurs often lack credible reputations, which causes potential customers to doubt their product's quality. Thus, even when considering a product with a clear superior value proposition, consumers will require significant effort from the entrepreneur before they adopt it. Entrepreneurs' reputations will grow as they sell more of their product, which in turn will make selling easier. However, in the early stages of selling, this shortage can pose a significant threat to sales success.

Finally, entrepreneurial firms lack established routines or processes because they are evolving organizations without codified work processes or assigned roles. For the selling process, this means that there are no established sales channels or previous customers that the firm can rely on. Instead, new relationships with sales channels and/or customers must be forged. The lack of established sales routines also makes the early stages of selling challenging for technology entrepreneurs.

In addition to these shortages, there are two key dynamics present in the market place that can potentially threaten the entrepreneur's product from reaching its commercial potential. These are embodied in the following example of a technology entrepreneur embarking on the selling process:[1]

> *The entrepreneur had successfully developed a prototype of an ultra-light, foldable, and chainless electric bike suitable for inner-city commutes. Since he had already secured some initial funding and taken advantage of his personal contacts and consequently had manufacturing capability in Eastern Europe, the entrepreneur's major concern was how to market the electric bikes in a large European city. Specifically, he wondered whether he should focus his time on selling to possibly influential consumers (e.g., young professionals and/or local municipalities in central-city areas) who could serve as free advertising to other potential customers, or whether he should take a more bottom-up approach. Additionally, how would existing electric bike manufacturers respond in the short term (e.g., by offering extended warranties), and how should the entrepreneur reassess his selling strategy to reflect any such responses?*

The first dynamic is *consumer peer learning*, which has been widely studied from a theoretical perspective [10] and observed in a variety of contexts [11, 12]. Although the product developed by the entrepreneur was highly innovative and arguably superior to what the market currently offered by virtue of being foldable and

[1] This illustrative example comes from a real entrepreneur who participated in a technology entrepreneurship program at our institution and with whom we had extensive discussions during the early stages of our research project.

chainless, consumers would still have doubts about the product's superior value. When a purchase decision involves uncertainty, consumers often rely on the purchases made by others [13-15]. The second dynamic is *incumbent reaction*, whereby incumbent firms employ a defensive strategy or other competitive responses to retain their customers [16, 17]. Because the new product was highly innovative and used a new technology, incumbents could not quickly develop a competing product of equal caliber in the short term. However, an incumbent firm might try a short-term strategy to deter the new entrant, e.g., by offering additional service or by lowering the prices of its existing products to enhance its customers' utility or surplus [18-20].

Our focus is on technology entrepreneurs (such as the one in the example) who have developed a functioning product or service and are embarking on the early stages of selling. We do not consider, for instance, technology entrepreneurs in the initial stages of development aiming at achieving certain milestones (e.g., FDA approval in the bio-tech industry). Moreover, we focus on settings where entrepreneurs are trying to demonstrate the viability of their new products in the market by generating initial sales. Thus, we do not consider technology entrepreneurs who can leverage past product sales records to partner with investors or outsource their sales activity. For the entrepreneurs we study, whether the opportunity presented by a promising product can be realized hinges on the entrepreneur's ability to manage the aforementioned shortages in resources, reputation, and routines and convert potential threats such as the incumbent reaction into opportunities during the early selling phase.

This paper aims to understand how entrepreneurs can achieve success in the early selling phase through the time allocation decisions they make. The key bottleneck resource for new ventures is often the entrepreneurs themselves, and how they allocate their time will therefore directly determine the firm's revenue, speed of growth, and ultimate size [21-23]. In particular, we address the following question: How should technology entrepreneurs allocate their limited time to potential consumers in order to maximize their short-term sales opportunities, given the two market dynamics of incumbent reaction and consumer peer learning? Put differently, how can an entrepreneur transform potential threats from incumbent reaction and opportunities from consumer peer learning into greater sales, given the significant time shortage?

To answer this question, we employ a mathematical model. We consider a stylized market consisting of two buyers (or two customer segments), each representing a different revenue amount upon a successful sale. The sales process is inherently uncertain, but the probability of a sale for each buyer increases with the amount of time the entrepreneur invests in selling to that buyer. Thus, we characterize entrepreneurial selling as an operational process that transforms the input of time into the output of expected sales. Our stylized market also incorporates the two market dynamics that offer opportunities/threats: (i) an influential (e.g., more visible) buyer's purchase decision can impact the purchase decision of a non-influential (e.g., less visible) buyer, and (ii) the incumbent can potentially react to retain its customers and lower the entrepreneur's chance of acquiring them. We investigate the optimal time allocation to maximize the entrepreneur's expected sales in the presence of consumer peer learning and/or incumbent reaction, studying the effect of each market dynamic separately as well as their interaction on the entrepreneur's optimal time allocation decision.

Our analysis reveals that the presence of consumer peer learning, when it is considered independently, encourages the entrepreneur to invest more selling time in the influential buyer to take advantage of the free advertising—indeed, entrepreneurs may prefer to invest more time in selling to influential buyers than to non-influential buyers even if selling to the former means *negative* revenue. Our analysis also reveals that the presence of incumbent reaction, when considered independently, encourages the entrepreneur to invest more selling time in the buyer who represents *smaller* revenue. Attempting to acquire the larger buyer is inefficient because the incumbent seeks to retain that buyer. When the two effects are considered together, we find that the market dynamics of consumer peer learning and incumbent reaction interact to present a non-monotonic relationship between sales time and expected sales. Specifically, entrepreneurs should focus their selling time on influential buyers when they represent either relatively small revenue or larger revenue than non-influential buyers. However, when an influential buyer represents slightly smaller revenue than a non-influential buyer, entrepreneurs should instead focus their sales time on the non-influential buyer.

The intuition behind the results when both dynamics are present is as follows. If the influential buyer represents small revenue compared to the non-influential one, the incumbent firm will seek to retain the larger non-influential buyer. In such a case, it is highly desirable for the entrepreneur to invest selling time in the small influential buyer, both to avoid direct competition with the incumbent and to take advantage of consumer peer learning. If the influential buyer represents larger revenue than the non-influential buyer, the entrepreneur should increase the selling time given to the larger influential buyer despite the incumbent's reaction aimed at retaining the buyer. This is because the prospect of acquiring larger revenue and free advertising offsets the reduced probability of a successful sale which is caused by the incumbent's reaction. When the influential buyer represents similar but smaller revenue than the non-influential buyer, the incumbent firm will react to retain the influential buyer in order to take advantage of consumer peer learning. In this case, the reduced revenue prospect and probability of success caused by the incumbent reaction offsets the potential gain from free advertising, making it less desirable to invest time in the smaller influential buyer. Thus, the entrepreneur should increase the selling time given to the non-influential buyer.

Our results demonstrate that for the entrepreneur, despite presentation of an objectively superior product to the market, the shortages and potential opportunities/threats make it less straightforward for the entrepreneur to monetize that product. For example, without considering the potential reaction of the incumbent, entrepreneurs may be tempted to focus their sales effort on the influential customer segment to take advantage of their free advertising. However, this could lead to the trap of "punching above their weight" and result in a reduced chance of success in initial sales, thus undermining the opportunity offered by the superior product. The size of the opportunity for a technology entrepreneur is inherently influenced by the market dynamics of consumer peer learning and incumbent reaction. By recognizing their shortages and managing opportunities and threats through informed decisions, entrepreneurs must shape their own opportunities.

II. RELATED LITERATURE

The entrepreneurship literature has highlighted the significant amount of time that entrepreneurs devote to sales. In a time allocation survey of early-growth stage entrepreneurs, one study has observed that entrepreneurs spend 38% of their time, the highest percentage for any activity, on direct selling and customer contact [24]. A recent study of entrepreneurs' everyday behavior has also observed similar patterns, with 31% of startup entrepreneurs' working time spent on communicating with external partners [7]. Building on these observations, we formalize the entrepreneur's time allocation decision when selling in order to study how entrepreneurs should allocate their limited time to potential customers to maximize expected sales.

Entrepreneurs are often cited as an organization's main bottleneck resource, and their time allocation decisions directly determine the firm's revenue, speed of growth, and ultimate size [21-23]. Accordingly, a large amount of literature dating back to the models in [25] and [26] has focused on entrepreneurs' time allocation decisions. Several studies examine how entrepreneurs allocate their time between the waged job, new ventures, and leisure via analytical [27], empirical [24, 28], and experimental [29, 30] approaches. The study in [22] examines how entrepreneurs should allocate their time to process improvement in order to better manage growth. Although these studies have enhanced our understanding of the intertemporal time allocation decisions of the entrepreneur, we believe that, considering the fact that technology entrepreneurs spend a considerable amount of their precious time solely on selling efforts [7, 24], time allocation for selling warrants specific attention. Consequently, this paper extends the literature on the entrepreneur's time allocation strategy by focusing on time spent on selling during entrepreneurial selling cycles, an important but understudied phenomenon in this domain.

In our study of the time allocation of entrepreneurs, we incorporate two critical potential opportunities/threats when selling new technology—peer influence via consumers' purchase behavior and competitive reactions by the incumbent firm—in a game-theoretic framework. The impact of consumer peer learning, which describes consumer herding behavior [10], as well as how firms should adjust their strategies in its presence have been widely studied in the context of established firms. For example, [31] examines the incumbent firm's intertemporal decision regarding whether to explore a new technology or exploit an established technology in the presence of consumer peer effects. Others have examined the role of consumer peer learning in influencing decisions such as those involving pricing [32, 33] and product launch timing [34]. However, it is unclear whether such findings in large firm settings generalize and apply to entrepreneurial selling where there are limited resources. Compared to large firms, entrepreneurial firms may have severely limited resources (e.g., time) for pursuing influential buyers in the first place; yet product purchases by influential buyers could be immensely helpful for entrepreneurs. In the context of entrepreneurial selling, where the seller lacks an established reputation, consumer peer learning arguably plays a more prominent role since an influential customer's purchase of a new product can compensate for the lack of reputation. Consequently, the present study focuses on how consumer peer learning provides a unique opportunity during the entrepreneurial selling process that is unlike the role it plays in the case of established firms.

Our study is also related to the literature on competitive market entry and incumbent reactions. Extensive research has addressed competitive responses and defensive marketing strategies [35-37]. A primary concern in this literature is the identification and examination of a variety of factors that could affect the likelihood and intensity of competitor responses [38-40]. These studies provide insights about the notion of competitive market entry, but their focus is mainly on large, established firms in traditional market contexts. Only recently have researchers begun to devote sustained attention to competitive strategies for entrepreneurial firms [41]; these include, inter alia, the timing of market entry [42, 43], entrepreneurial risk [44], integration into complementary technologies [45], and pre-entry resources [46]. Entrepreneurs may also be more selective about their actions and therefore less likely to engage in costly and frequent competitive moves [41]. Our paper complements this stream of research by examining asymmetric strategy sets for the entrepreneur and the incumbent in competing for customers. In addition, while this stream of research is primarily concerned with exploitative and exploratory moves in competition [41], our work incorporates consumer peer learning and investigates the implications of the interplay between competition and peer learning.

III. MODEL SETUP

We consider a stylized market consisting of two rational consumers (Buyer 1 and Buyer 2) representing different levels of revenue (R_1 and R_2, respectively) and peer influence. Alternatively, Buyer 1 and Buyer 2 can be interpreted as two distinct consumer groups, with R_1 and R_2 representing the collective revenue derived from each. While R_1 and R_2 are exogenously given, it is uncertain whether the entrepreneur can capture those revenues. Thus, the entrepreneur is interested in the expected revenues $E[R_1]$ and $E[R_2]$, which are increasing in the sales efforts n_1 and n_2 directed to Buyer 1 and Buyer 2, respectively.

Both of the buyers are customers of the incumbent firm, which may react to the entrepreneur's market entry by providing these customers with added benefits k_1 and k_2 aimed at retaining Buyer 1 and Buyer 2, respectively. The scenario is illustrated in Figure 1.

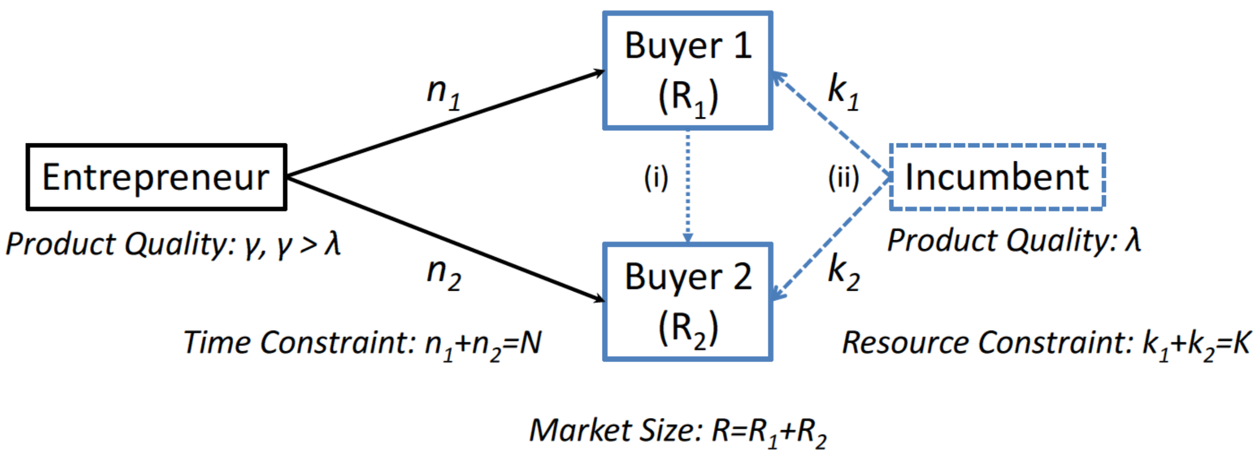

Fig. 1. Entrepreneur's time allocation problem with (i) consumer peer learning and (ii) incumbent reaction.

The technology entrepreneur is equipped with a superior substitutable product or a service (hereafter, simply "product"). In order to focus on the entrepreneur's time allocation decision, we assume vertically differentiated products characterized by exogenous parameters γ and λ representing the value propositions of the entrepreneur's and the incumbent's product, respectively. Thus, when making a purchase decision, each consumer compares the value proposition of the entrepreneur's product (γ) with that of the incumbent's product (λ) (see, for example, [47, 48]).

The entrepreneur's product is superior ($\gamma > \lambda$), due to either higher quality at a similar price or similar quality at a lower price. For example, an entrepreneur might offer a higher-performing algorithm at the prevailing price point or a less expensive data storage system with the latest levels of capacity and functionality. However, unlike the incumbent firm's product quality λ, which is known to the buyers, the entrepreneur's product quality γ is unknown.

To make a successful sale, the entrepreneur must invest time (in the form of meetings, phone calls, etc.) to help potential buyers learn about the new product's superior value. The process of selling entails high uncertainty, and thus the time invested may not result in a sale. To capture the randomness, we model the selling process via a "sampling" process, where the entrepreneur's allocated time is represented by the amount of information (samples of the product value) provided to each buyer. Specifically, when the entrepreneur directs n_i units of time (e.g., number of hours) to Buyer *i*, Buyer *i* observes the samples, $X^1, X^2, \ldots, X^{n_i}$, which are independently and identically distributed (i.i.d.) with mean γ and variance σ^2. This variance term can be considered as the effect of reputation, with larger variance indicating smaller reputation—that is, consumers will interpret the entrepreneur's sales messages in a more mixed manner if the entrepreneur lacks a credible reputation.

Based on the information given, buyers form their beliefs about the new product's value proposition. The distribution of the sample mean will be a normal distribution due to the central limit theorem, so if the entrepreneur decides to exert a sample size of n_i units of time, Buyer *i*'s belief about the product value is a random quantity $\hat{\gamma}_i \equiv \frac{\sum_{j=1}^{n_i} X^j}{n_i} \sim \mathrm{N}(\gamma, \frac{\sigma^2}{n_i})$. Buyer *i* will purchase from the entrepreneur if and only if Buyer *i* is convinced that the expected product value exceeds the value derived from the incumbent's product, i.e., $\hat{\gamma}_i > \lambda$. The probability of a purchase by Buyer *i* after being given n_i samples is therefore

$$P(\hat{\gamma}_i > \lambda \mid n_i) = \Phi(\frac{\gamma - \lambda}{\sigma}\sqrt{n_i}),$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. Thus, when the entrepreneur devotes more time (larger n_i) to Buyer i, the buyer's belief regarding the quality $\hat{\gamma}_i$ will approach the true quality γ as its variance decreases. In other words, reducing uncertainty about the product quality improves the entrepreneur's chance of completing a sale; however, it does not guarantee it.

The term $(\gamma-\lambda)/\sigma$ represents how easy it is to acquire a buyer. The larger the value of this fraction, the easier it is for the entrepreneur to convince Buyer i. We shall use the symbol $\Delta \equiv (\gamma-\lambda)/\sigma$ where needed, for simplicity of expression.

The entrepreneur seeks to maximize the expected revenue by optimally allocating efforts n_1 and n_2 to Buyer 1 and Buyer 2 in an attempt to realize revenues R_1 and R_2 from them. Because the entrepreneur's time is limited, i.e., $n_1 + n_2 = N$ for some N, the entrepreneur's Time Allocation Problem (TAP) is

$$\max_{n_1, n_2} E\pi_{\mathrm{E}} = \sum_{i=1,2} R_i \cdot P(\hat{\gamma}_i > \lambda \mid n_i).$$

The entrepreneur's TAP is complicated by two effects, consumer peer learning and the incumbent's response, which we formally examine in the rest of this section. The sequence of events is summarized in Figure 2.

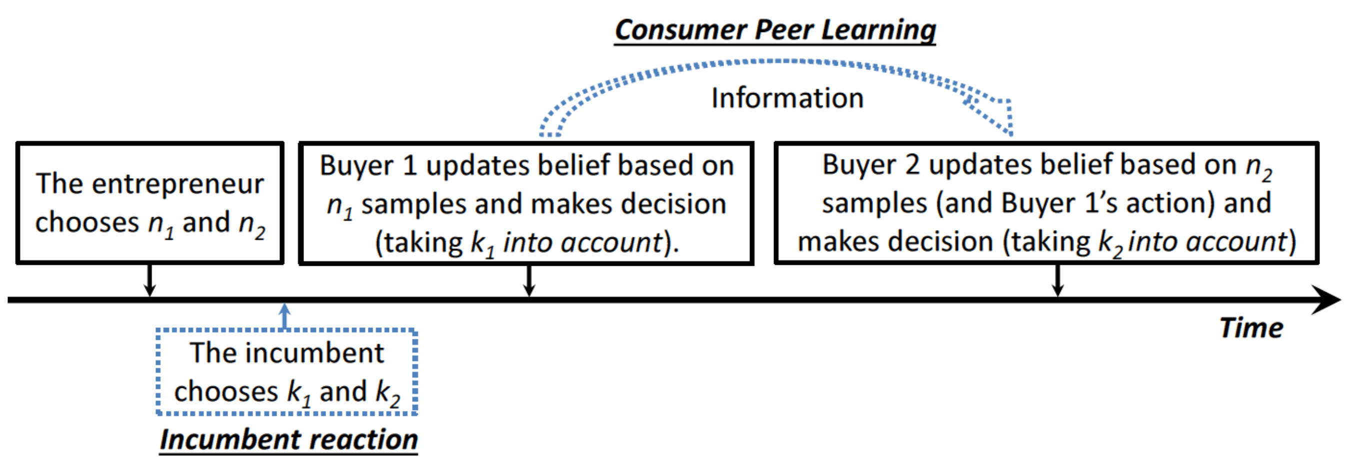

Fig. 2. Sequence of events. The dotted elements signify possible actions of the incumbent or consumers.

A. Consumer Peer Learning

We assume that the two buyers have different levels of peer influence. In this case, a purchase by the more influential buyer (Buyer 1) may well prompt the other, non-influential, buyer (Buyer 2) to also decide to purchase. In other words, a sale to the more influential buyer makes a sale to the non-influential buyer more likely.

Suppose that the entrepreneur-provided information n_1 convinces Buyer 1 to buy the new product. Then the more influential Buyer 1's act of purchasing affects Buyer 2's purchase decision. We model this consumer peer learning as Buyer 2 inferring Buyer 1's information and using it—along with its own information n_2 supplied by the entrepreneur—to update its beliefs about the new product.[2] Thus, a purchase from the entrepreneur by Buyer 1 may prompt Buyer 2 to make a purchase even if Buyer 2 would not have purchased when taking only its own information about the product into account. The information inferred may be partial; however, for simplicity, we assume—as in [49]—that the information is complete.

In the presence of consumer peer learning, Buyer 2's belief about the product value proposition depends on whether or not Buyer 1 has purchased, as follows:

$$\hat{\gamma}_2 = \begin{cases} \dfrac{\sum_{j=1}^{n_1} X^j + \sum_{j=1}^{n_2} X^j}{n_1 + n_2} \sim \mathrm{N}(\gamma, \dfrac{\sigma^2}{N}) & \text{if Buyer1 has purchased;} \\ \dfrac{\sum_{j=1}^{n_2} X^j}{n_2} \sim \mathrm{N}(\gamma, \dfrac{\sigma^2}{n_2}) & \text{if Buyer1 has not purchased,} \end{cases}$$

so the purchase probability for Buyer 2 becomes

[2] We do not focus on the seemingly analogous case in which Buyer 1's decision *not* to purchase from the entrepreneur makes it less likely that Buyer 2 does so. The reason is that the influential buyer's decision not to purchase is less observable than an actual purchase. Furthermore, entrepreneurs actively advertise their successful cases (e.g., by listing customers on their websites) but have no motivation to publicly acknowledge unsuccessful ones.

$$P(\hat{\gamma}_2 > \lambda) = P(\frac{\sum_{j=1}^{n_1} X^j + \sum_{j=1}^{n_2} X^j}{n_1+n_2} > \lambda) \cdot P(\frac{\sum_{j=1}^{n_1} X^j}{n_1} > \lambda) + P(\frac{\sum_{j=1}^{n_2} X^j}{n_2} > \lambda) \cdot P(\frac{\sum_{j=1}^{n_1} X^j}{n_1} < \lambda)$$

$$= \Phi(\frac{\gamma-\lambda}{\sigma}\sqrt{N}) \cdot \Phi(\frac{\gamma-\lambda}{\sigma}\sqrt{n_1}) + \Phi(\frac{\gamma-\lambda}{\sigma}\sqrt{n_2}) \cdot \Phi(-\frac{\gamma-\lambda}{\sigma}\sqrt{n_1}).$$

B. Incumbent Reaction

As the entrepreneur attempts to acquire buyers, the incumbent may react in order to retain its customers. Because we focus on short-term strategies, the incumbent's possible reaction is limited to a marginal increase in its product value proposition through additional benefits or a reduced price. Specifically, the incumbent can provide an additional benefit k_i to buyer *i* to enhance the product value proposition (e.g., loyalty benefits, reimbursement, extra service, better after-sales technical support, or selective price markdowns). The likelihood of Buyer *i* not buying from the entrepreneur is

$$P(\hat{\gamma} < \lambda + k_i \mid n_i).$$

Clearly, this expression is increasing with k_i .

The incumbent also has limited short-term resources that can be used for buyer retention, so $k_1 + k_2 = K$ for some *K*; if the incumbent had unlimited resources, the entrepreneur would have no chance of succeeding in the market and should therefore refrain from entering it. This constraint creates a trade-off for the incumbent firm in its decision, which is aimed at increasing the likelihood of retaining customers and maximizing its expected revenue $E\pi_{\text{I}}$. The incumbent firm's optimal response to the entrepreneur's time allocation strategy (n_1, n_2) involves solving the Incumbent Reaction Problem (IRP):

$$\max_{k_1,k_2} E\pi_{\text{I}} = \sum_{i=1,2} R_i \cdot P(\hat{\gamma}_i \le \lambda + \mathrm{k_i} \mid n_i)$$

A distinctive feature of the customer acquisition/retention game modeled here is that the entrepreneur and the incumbent implement asymmetric strategy sets. The entrepreneur strives to reduce customers' uncertainty (the variance of their belief about the product's value proposition) by allocating time to educate them about the new product's superiority. The incumbent, on the other hand, tries to marginally increase its product value proposition (shift the distribution) by adding services (or lowering prices), which is intended to deter the entrepreneur from selling its product.

We shall assume that neither the entrepreneur nor the incumbent has sufficient time/resources to induce purchasing by both buyers:

Assumption 1. (i) $N \leq \sigma^2/(\gamma-\lambda)^2$; (ii) $K < \gamma - \lambda$.

This assumption allows us to focus on our setting of interest, namely, the setting in which the entrepreneur and the incumbent must each make a decision involving a trade-off. Specifically, part (i) ensures that the entrepreneur does not have enough time (N) to significantly increase the purchase probability of both buyers (either because the entrepreneur's reputation is low, i.e., the value of σ is high, or because the level of superiority of the entrepreneur's product is low, i.e., $(\gamma-\lambda)$ is small), so that the entrepreneur needs to decide how best to allocate its time, while part (ii) guarantees that the incumbent cannot match the superior quality of the entrepreneur's new product by providing additional benefits to the buyers, since otherwise the entrepreneur would not have any opportunity to make a sale in the market.

Considering that the resource constraint is always binding (it is rational for the entrepreneur and the incumbent to use all the resources that they have: $n_1 + n_2 = N$ and $k_1 + k_2 = K$), we can then characterize the allocation decision in terms of a single decision variable. We adopt the convention of focusing on the resources allocated to (the more influential) Buyer 1—that is, on n_1 and k_1. We treat n_1 and k_1 as continuous variables when solving for the optimal effort and resource allocation strategies, in line with the conventional practice in the modeling literature (see, e.g., [50]).

IV. Analysis and Results

In our analysis, we analyze four types of markets, based on the presence or absence of consumer peer learning and incumbent reactions. By analyzing the optimal time allocation strategy for each scenario, our framework helps us understand the influence of each dynamic independently as well as the interaction between the two dynamics by providing an economic rationale.

We use the superscripts '*L', '*R', and '*LR' to signify (respectively) the optimal time allocation with learning only, incumbent reaction only, and both learning and incumbent reaction; this will distinguish these three cases from the base case, for which the superscript '*' is used. We first examine the entrepreneur's time allocation decision in the base case (all proofs are given in the Appendix.)

A. Base Case (Benchmark)

In this case, buyers make decisions based only on the time allocated to them by the entrepreneur. The TAP therefore becomes

$$\max_{n_1} E\pi_{\mathrm{E}} = R_1 \cdot \Phi(\Delta\sqrt{n_1}) + R_2 \cdot \Phi(\Delta\sqrt{N-n_1}). \tag{1}$$

The next result characterizes the optimal allocation strategy.

Proposition 1. *The entrepreneur's unique optimal time allocation* n_1^* *to Buyer 1 satisfies the following equality (where* $\Phi'(\cdot)$ *is the first derivative of* $\Phi(\cdot)$*):*

$$\frac{R_1}{\sqrt{n_1}} \cdot \Phi'(\Delta\sqrt{n_1}) = \frac{R_2}{\sqrt{N-n_1}} \cdot \Phi'(\Delta\sqrt{N-n_1}). \tag{2}$$

The dotted curve in Fig. 3 plots the optimal proportion of time invested in Buyer 1 (n_1^*/N) as a function of the ratio R_1/R_2 on a logarithmic scale. The curve confirms our intuition that more time should be allocated to the buyer who represents greater revenue. The curve is symmetric around $R_1/R_2 = 1$, with exactly half of the time being given to each of Buyer 1 and Buyer 2 if $R_1 = R_2$. This follows from Eq. (2): an increase in R_1 increases the left-hand side of Eq. (2), leading to a larger n_1^*, while an increase in R_2 increases the right-hand side of Eq. (2), leading to a smaller n_1^*.

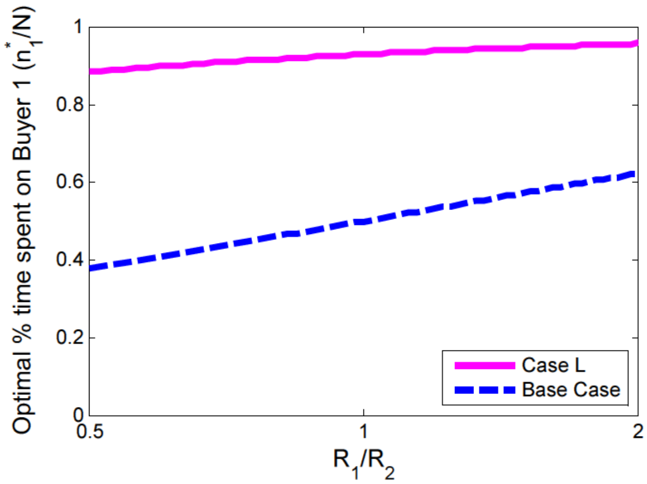

Fig. 3. Effect of consumer peer learning. Optimal % time spent on Buyer 1 plotted as a function of R_1/R_2 on a log scale for case L (solid curve) and base case (dotted curve). Parameters: N=200, γ =5, λ=4.85, σ=2.25, $R_1 \in [50,200]$, $R_2 = 100$.

B. Consumer Peer Learning (Case L)

In the presence of consumer peer learning, the likelihood of Buyer 2 purchasing the entrepreneur's product also depends on Buyer 1's decision. This is because Buyer 1's purchase provides assurance to Buyer 2 regarding Buyer 2's uncertainty about the product's quality, in essence acting as "free advertising." Considering this dynamic, the entrepreneur's TAP becomes:

$$\max_{n_1} E\pi_{\mathrm{E}} = R_1 \cdot \Phi(\Delta\sqrt{n_1}) + R_2 \cdot \Phi(\Delta\sqrt{N-n_1}) + R_2 \cdot (\Phi(\Delta\sqrt{N}) - \Phi(\Delta\sqrt{N-n_1})) \cdot \Phi(\Delta_1\sqrt{n_1}) \quad (3)$$

In contrast to the base case, as described in Eq. (1), the entrepreneur must now consider the additional term $R_2 \cdot (\Phi(\Delta\sqrt{N}) - \Phi(\Delta\sqrt{N-n_1})) \cdot \Phi(\Delta\sqrt{n_1}) \geq 0$. The expression $(\Phi(\Delta\sqrt{N}) - \Phi(\Delta\sqrt{N-n_1}))$ describes the increase in Buyer 2's probability of purchasing that results from Buyer 1's purchase. Thus, the entrepreneur's effective revenue from convincing Buyer 1 amounts to

$$\Re_1 = R_1 + R_2(\Phi(\Delta\sqrt{N}) - \Phi(\Delta\sqrt{N-n_1})).$$

The effective revenue comprises R_1, the *direct* revenue from Buyer 1, and $R_2(\Phi(\Delta\sqrt{N}) - \Phi(\Delta\sqrt{N-n_1}))$, the *indirect* revenue from Buyer 2 achieved through peer learning. Absent peer learning, Buyer 2 would glean no information from Buyer 1's purchase and so the indirect revenue term would disappear, which would reduce Eq. (3) to the base case of Eq. (1). The effective revenue from Buyer 1 ($\Re_1$) increases with the entrepreneur's allocated time (n_1).

The next result formalizes how consumer peer learning influences the entrepreneur's sales strategy.

Proposition 2. *The optimal time allocation to Buyer 1 under consumer peer learning,* n_1^{*L}, is greater than or equal to n_1^*. *Moreover,* n_1^{*L} *satisfies the following equality:*

$$\frac{1}{\sqrt{n_1}}\cdot\frac{\Phi'(\Delta\sqrt{n_1})}{1-\Phi(\Delta\sqrt{n_1})}=\frac{1}{\sqrt{N-n_1}}\cdot\frac{\Phi'(\Delta\sqrt{N-n_1})}{(R_1/R_2+\Phi(\Delta\sqrt{N}))-\Phi(\Delta\sqrt{N-n_1})}. \tag{4}$$

The solid curve in Fig. 3 plots the optimal proportion of time allocated to Buyer 1 (n_1^{*L}/N) as a function of the revenue ratio R_1/R_2 in the presence of consumer peer learning. Compared to the base case (the dotted curve), the optimal proportion of time to invest in Buyer 1 is significantly higher (around 90%) because Buyer 1 represents more revenue when there is consumer peer learning than when there is not (i.e., $\Re_1 \geq R_1$).

The entrepreneur should allocate more time to Buyer 1 than Buyer 2 even if $R_1 < R_2$. In fact, one can observe from the right-hand side of Eq. (4) that the entrepreneur may want to allocate more time to Buyer 1 than Buyer 2 even if $R_1 < 0$.[3] This represents the case of the entrepreneur investing time to convince Buyer 1 *and paying* for Buyer 1's endorsement.

C. Incumbent Reaction (Case R)

Recall that the incumbent may react by providing an additional benefit k_i to Buyer *i*. By providing this benefit, the incumbent alters the superiority of the entrepreneur's product for Buyer *i* to $\Delta(k_i) := [\gamma-(\lambda+k_i)]/\sigma.$ Note that this expression is decreasing in k_i, i.e., a stronger incumbent reaction

[3] From the right-hand side of Eq. (4), because $\Phi(\Delta\sqrt{N})-\Phi(\Delta\sqrt{N-n_1})\geq 0$, it follows that the entrepreneur should invest time to seek Buyer 1's endorsement as long as R_1/R_2 is not strongly negative.

makes it more difficult for the entrepreneur to acquire buyers. We will use the notation $\Delta(k_i)$ to make this dependence explicit where appropriate.

Applying the principle of backward induction, we first examine the incumbent reaction problem (IRP),

$$\max_{k_1} E\pi_{\mathrm{I}} = R_1 \cdot \left(1-\Phi(\Delta(k_1)\sqrt{n_1})\right) + R_2 \cdot \left(1-\Phi(\Delta(K-k_1)\sqrt{N-n_1})\right) . \tag{5}$$

The incumbent's optimal strategy is formalized next.

Lemma 1. *Given the entrepreneur's time allocation strategy, the incumbent's optimal strategy is*

$$k_1^* = \begin{cases} K & \text{if } R_1/R_2 \geq \Upsilon^{\mathrm{R}}(n_1); \\ 0 & \quad \textit{otherwise}, \end{cases}$$

where $\Upsilon^{\mathrm{R}}(n_1) \equiv \dfrac{\Phi(-\Delta(K)\sqrt{N-n_1}) - \Phi(-\Delta(0)\sqrt{N-n_1})}{\Phi(-\Delta(K)\sqrt{n_1}) - \Phi(-\Delta(0)\sqrt{n_1})}$.

Lemma 1 states that it is optimal for the incumbent to adopt an all-or-nothing approach, i.e., to dedicate all its resources *K* to either Buyer 1 or Buyer 2, depending on whether or not the ratio R_1/R_2 is above a threshold $\Upsilon^{\mathrm{R}}(n_1)$, which depends on the entrepreneur's time allocation. Specifically, the numerator of $\Upsilon^{\mathrm{R}}(n_1)$ represents the increase in the incumbent's chance of retaining Buyer 2 when all its resources are dedicated to Buyer 2, and the denominator of $\Upsilon^{\mathrm{R}}(n_1)$ represents the increase in the incumbent's chance of retaining Buyer 1 when all its resources are dedicated to Buyer 1. Therefore, if $R_1/R_2 \geq \Upsilon^{\mathrm{R}}(n_1)$, then dedicating all resources to Buyer 1 is more beneficial than dedicating all to Buyer 2.

The next result formalizes how the incumbent's reaction influences the entrepreneur's optimal sales strategy.

Proposition 3 . *The optimal time allocation to Buyer 1 under the incumbent's reaction,* $n_1^{*\mathrm{R}}$, *is less than* n_1^* *if and only if* $R_1/R_2 > 1$.

Proposition 3 shows that in the presence of incumbent reaction, the entrepreneur should always focus on the buyer representing *smaller* revenue; this is because the incumbent will always focus its resources on retaining the buyer representing larger revenue. In other words, the entrepreneur should refrain from directly competing with the incumbent. The reason is that it is easier for the incumbent to retain an existing buyer than for the entrepreneur to acquire a new one. To see this, suppose the entrepreneur wants to maintain Buyer 1's probability of purchasing at ω, i.e., $\Phi(\Delta(k_1)\cdot\sqrt{n_1})=\omega$. The expression inside the parentheses is linear in k_1 but involves the square root of n_1. So if the incumbent allocates K to Buyer 1, then the entrepreneur must allocate significantly more of its limited time to n_1 simply to remain competitive. But without a clear assurance of acquiring Buyer 1, it is clearly inefficient to sacrifice Buyer 2. This finding is similar in spirit to a finding in [41], which argues that new entrants perform better when they avoid triggering countermoves by large rivals.

The solid curve in Fig. 4 plots the optimal proportion of time allocated to Buyer 1 (n_1^{*R}/N) as a function of the ratio R_1/R_2 in the presence of incumbent reaction. Compared to the base case (dotted curve), there is a discontinuous drop at $R_1/R_2 = 1$, which represents the equilibrium ratio: the ratio $\Upsilon^R = 1$ represents the point where the incumbent is indifferent between dedicating resources to Buyer 1 or to Buyer 2, and when $R_1 = R_2$, as shown in the base case, the entrepreneur should allocate time equally between the two buyers ($n^R = N - n^R$). When $R_1 < R_2$, the incumbent prefers to allocate all its resources to retain Buyer 2; hence the entrepreneur should avoid Buyer 2 and increase the sales time allocated to Buyer 1 compared to the base case. Conversely, if $R_1 > R_2$, then the incumbent will instead put all its sales resources into retaining Buyer 1; in this case, the entrepreneur should increase the sales time it allocates to Buyer 2, which would yield a higher return on the entrepreneur's time.

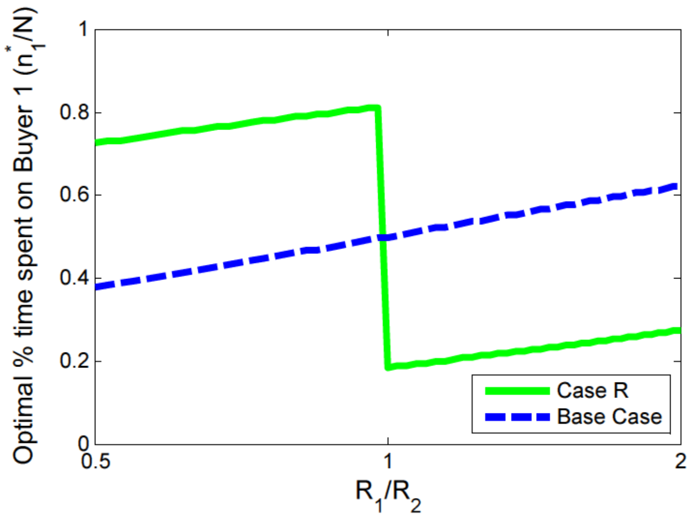

Fig. 4. Effect of incumbent reaction. Optimal % time spent on Buyer 1 plotted as a function of R_1/R_2 on a log scale for case R (solid curve) and base case (dotted curve). Parameters: N=200, γ =5, λ=4.85, σ=2.25, K=0.1, $R_1 \in [50,200]$, $R_2 = 100$.

D. Interaction of Consumer Peer Learning and Incumbent Reaction (Case LR)

We now examine the interaction of the two effects of consumer peer learning and incumbent reaction. Again, following the principle of backward induction, we first examine the incumbent's reaction problem in the presence of consumer peer learning, which is now:

$$\max_{k_1} E\pi_{\mathrm{I}} = R_1 \cdot (1-\Phi(\Delta(k_1)\sqrt{n_1})) + R_2 \cdot (1-\Phi(\Delta(\mathrm{K}-k_1)\sqrt{N})) \cdot \Phi(\Delta(k_1)\sqrt{n_1})$$

$$+ R_2 \cdot (1-\Phi(\Delta(K-k_1)\sqrt{N-n_1})) \cdot (1-\Phi(\Delta(k_1)\sqrt{n_1})) . \tag{6}$$

The incumbent's best response is formalized next.

Lemma 2. *Given the entrepreneur's time allocation strategy* n_1, *the incumbent's optimal strategy is*

$$k_1^* = \begin{cases} K & \text{if} \;\; R_1/R_2 \geq \Upsilon^{\mathrm{LR}}(n_1); \\ 0 & \quad\quad \text{otherwise,} \end{cases}$$

where $\Upsilon^{\mathrm{LR}}(n_1) < 1$.

We refer readers to Eq. (A.2) in the appendix for the expression of $\Upsilon^{\mathrm{LR}}(n_1)$. The influence of consumer peer influence on the incumbent's reaction is reflected in the strict inequality $\Upsilon^{\mathrm{LR}} < \Upsilon^{\mathrm{R}} = 1$. This implies that the incumbent is willing to dedicate all its resources to Buyer 1 even if this buyer represents smaller revenue than Buyer 2 ($R_1 < R_2$), because consumer peer learning increases the effective revenue from Buyer 1 ($\Re_1 \geq R_1$).

We next characterize how consumer peer learning and the incumbent's reaction interact to influence the entrepreneur's time allocation decision.

Proposition 4. *There exists* $\Upsilon^{*LR} < 1$ *such that*

(i) $n_1^{*LR} > n_1^{*L}$ *if and only if* $R_1/R_2 < \Upsilon^{*LR}$ *, and*

(ii) $n_1^{*LR} > n_1^{*R}$ *if* $R_1/R_2 < \Upsilon^{*LR}$ *or* $R_1/R_2 > 1$.

Part (i) of Proposition 4 shows the marginal impact of the incumbent's reaction in the presence of peer learning. This is illustrated in the left panel of Figure 5. The optimal proportion of time invested in Buyer 1 in the presence of both consumer peer learning and incumbent reaction (case LR, solid curve) and with only consumer peer learning (case R, dash-dot curve) are plotted with respect to R_1/R_2 on a logarithmic scale. Recall that in case L (the dotted curve), it is optimal for the entrepreneur to invest a significant proportion (around 90%) of its time in the influential Buyer 1 due to the effect of consumer peer learning. Relative to this benchmark, the presence of incumbent reaction encourages the entrepreneur to avoid directly competing with the incumbent, similar to Proposition 3. However, observe that avoiding direct competition with the incumbent no longer means that the entrepreneur should focus on the smaller buyer. The incumbent now seeks to retain the influential Buyer 1 in order to take advantage of free advertising even if it represents smaller revenue ($R_1 < R_2$). Thus, the entrepreneur can avoid competition for Buyer 1 only when it represents significantly smaller revenue ($R_1/R_2 < 0.8$).

Part (ii) of Proposition 4 shows the marginal impact of consumer peer learning in the presence of incumbent reaction. Recall that in Proposition 2, the presence of consumer peer learning always encourages the entrepreneur to invest more selling time in the influential Buyer 1. We find that this is no longer the case in the presence of incumbent reaction. This is illustrated in the right panel of Figure 5. Specifically, compared to case R (the dotted curve), when consumer peer learning is introduced, the entrepreneur should invest more time in the influential buyer only when $R_1/R_2$is either low ($R_1/R_2 < 0.8$) or high ($R_1/R_2 > 1$); for the intermediate range $R_1/R_2 \in (0.8,1)$, the entrepreneur should instead decrease the sales time allocated to the influential Buyer 1.

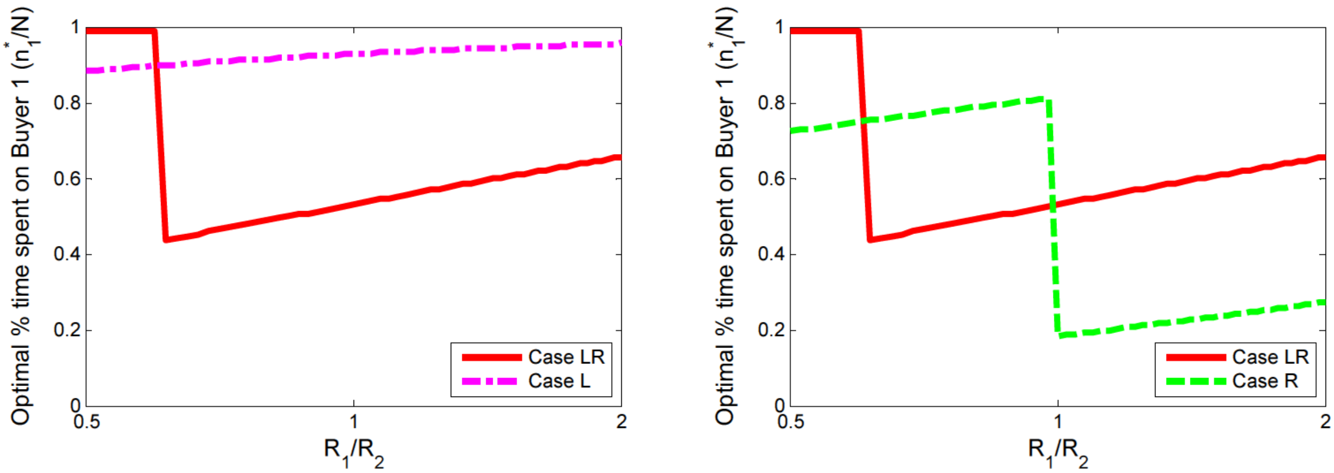

Fig. 5. Interaction (marginal) effect of consumer peer learning (right panel) and incumbent reaction (left panel). Optimal % time spent on Buyer 1 plotted as a function of R_1/R_2 on a log scale for case LR (solid curve), with case L (dash-dot curve) [left panel] and case R (dotted curve) [right panel]. Parameters: N=200, γ =5, λ=4.85, σ=2.25, K=0.1, $R_1 \in [50,200]$, $R_2 = 100$.

When Buyer 1 represents relatively small revenue ($R_1/R_2 < 0.8$), even its influential status does not make it attractive for the incumbent. In this case, the entrepreneur should maximize its chance of acquiring Buyer 1 by allocating even more time to Buyer 1 (close to 100%). If the influential Buyer 1 represents higher revenue ($R_1/R_2 > 1$), the incumbent will want to retain Buyer 1. In this case, it is desirable for the entrepreneur to increase its sales effort directed to the influential Buyer 1 to target higher revenue and to take advantage of Buyer 1's influence. When the influential buyer has neither low nor higher revenue potential, the incumbent firm will react to retain the influential buyer to take advantage of consumer peer learning. For the entrepreneur, due to Buyer 1's relatively lower revenue compared to Buyer 2 and the need to avoid competing with the incumbent, it is desirable to divert sales effort from the influential Buyer 1 to the non-influential Buyer with slightly higher revenue potential.

V. Discussion

Our research has implications for both theory and practice. Our research focuses on the market entry strategy and challenges faced by entrepreneurial firms. While extant research on new product market entry strategies has largely examined the setting of large established firms and the performance implications of various competitive moves [51, 52], the entrepreneurial firm setting requires a different focus on two fronts. First, entrepreneurial firms lack the resources, reputation, and routines of established firms [8], so their market entry will necessarily avoid moves that will require substantial economies of scale or experience curves [53-55]. Therefore, competitive moves between new entrepreneurial ventures and large firms are *asymmetric* [41, 56]. Second, a key notion in recent work on entrepreneurs in established markets has been their uphill battle against incumbents whose resources help them 'maintain dominance'. Entrepreneurs must be flexible in their entry in order to work around established rivals [41]. Thus, how entrepreneurs make their *tactical*-level decisions to manage their shortages in the face of opportunities/threats determines the size of their realized opportunity.

Building on this perspective, we examine the asymmetric customer acquisition versus retention setting between a technology entrepreneur and the incumbent, and we focus on the more granular operational-level decision regarding how entrepreneurs should allocate their limited selling time. Our results demonstrate that tactical-level decisions require understanding the nuances of the market dynamics and their interactions. For example, entrepreneurs should avoid competing directly with the incumbent for a customer segment, unless that segment represents both influential *and* large revenue. Furthermore, knowing whether or not an incumbent firm will react to the entrepreneur's entry has implications for the entrepreneur's tactical decisions. Thus, being knowledgeable about the incumbent is a key asset for entrepreneurs.

Our study also provides insights into consumer peer learning during new product sales. Previous research has predominantly suggested focusing first on people with a disproportional effect on others, often labeled "opinion leaders" or "influencers" [57, 58]. The idea is that convincing opinion leaders early in the sales process will help accelerate the adoption and usage of the product in the larger population. Our results, however, point to a more complex dynamic in which targeting the less influential customer may be the entrepreneur's optimal tactical move.

Because tactical-level decisions made by entrepreneurs are hard to observe empirically, previous research has made use of novel methods such as experiential simulations [41]. In our study, we employ a mathematical model. Mathematical models can be effective tools for building new theories of entrepreneurship because they can facilitate the articulation of assumptions and relationships among variables, while their optimal solutions provide a platform for developing testable hypotheses [59]. In this regard, our model can provide a platform for examining whether some uncertainty between sales effort and sales success can be explained by whether or not time has been allocated properly, depending on the different market dynamics.

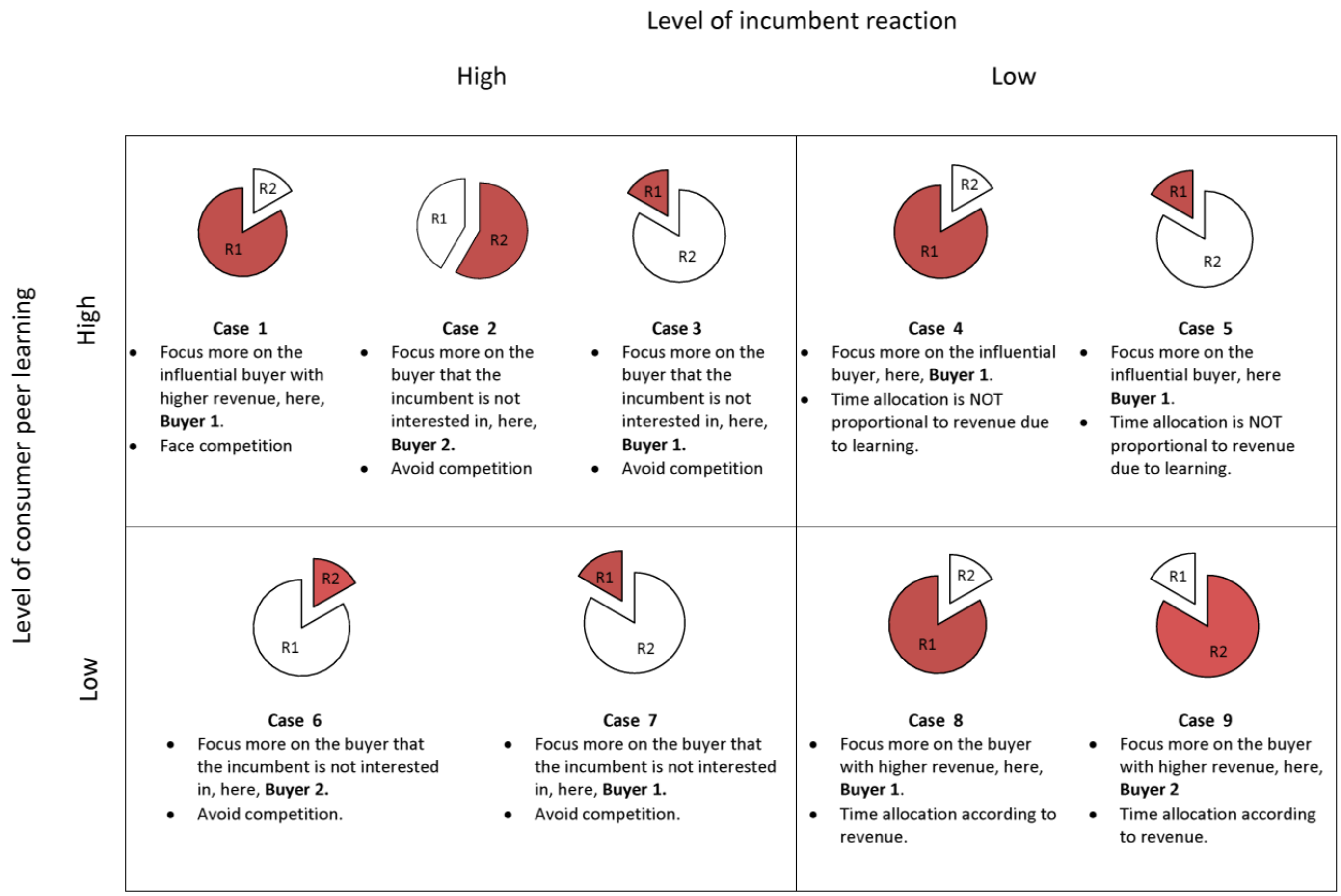

Fig. 6. The entrepreneur's time allocation strategy, depending on nine different market structures. The pie segments denoted as R_1 and R_2 show the relative size of revenues from the influential buyer (Buyer 1) and the other buyer (Buyer 2), respectively. Shaded pie segments correspond to the recommended selling focus for entrepreneurs.

The results of our analysis of the four cases naturally map into a practical rule of thumb (illustrated in Figure 6) that technology entrepreneurs can use for their market entry. Specifically, they can determine which of the nine cases (presence or absence of consumer peer learning and incumbent reaction, along with the revenue distribution of the buyers) matches their context most closely and focus their time on the buyer represented by the shaded portion of each pie. In the base case (lower right quadrant of the figure), it is preferable to focus more on the buyer that represents greater revenue. For the case with consumer peer learning only (upper right quadrant), it is preferable to focus more on the influential buyer even if this buyer represents less revenue. This can be seen by comparing Case 5 and Case 9. Entrepreneurs who exploit consumer peer learning increase their potential total revenue, and for a given market size the case with consumer peer learning is more promising than the one without.

In the case with incumbent reaction only (lower left), it is preferable to focus on the buyer that the incumbent would be *least* interested in. With a limited consumer peer learning effect, the incumbent pays more attention to the buyer who represents greater revenue; hence the entrepreneur should focus on selling to the buyer representing *smaller* revenue. The contrast with the prescriptions of the base case is seen by comparing Case 6 and Case 8 (or equivalently, Case 7 and Case 9). An entrepreneur can improve the return on its time by forgoing (or at least minimizing) direct competition with a reactive incumbent. For a given market size, the case featuring incumbent reaction will be less attractive than the alternatives.

Finally, when both consumer peer learning and incumbent reaction are in play (upper left quadrant), the decision is nuanced. If the more influential Buyer 1 represents a large portion of the market revenue (Case 1), then the entrepreneur should focus on Buyer 1 despite the competition with the incumbent because the level of influence and high revenue is sufficiently attractive. If the influential Buyer 1 represents a small portion of the market revenue (Case 3), then the entrepreneur should again focus on Buyer 1 to avoid direct competition with the incumbent (who now focuses on retaining Buyer 2) and to benefit from the potential "free advertising" to Buyer 2 provided by Buyer 1's purchase. If the influential Buyer 1 represents a slightly smaller portion of market revenue (Case 2), then the entrepreneur should focus on Buyer 2 to target a larger revenue and avoid competing with the incumbent for Buyer 1.

VI. CONCLUDING REMARKS

Our paper investigates the complex factors that should be considered by technology entrepreneurs seeking to allocate time among potential buyers when entering an established market with a superior product substitute. Because the entrepreneur offers a product that is truly superior to that of the incumbent, it might seem that it would only be a matter of time before the entrepreneur conquers the market. To do this, however, entrepreneurs must recognize and tactfully manage their shortages (in resources, reputation, and routines) to navigate through various threats and opportunities presented in the market. Equipped with a superior technology-based product, their goal in the early phase is to create initial sales. The first step in the technology entrepreneur's sales plan is identification of which potential customers should be approached first, and how. The research reported here addresses these questions by considering two major opportunities/threats found in many entrepreneurial market entry situations: the effect of influential customers on other potential customers and the incumbent's reaction to defend its market share.

This study offers economic insights into operational entrepreneurship, or "the selection and management of transformation processes for recognizing, evaluating, and exploiting opportunities for potential value creation" [60]. Specifically, focusing on the management of entrepreneurial selling—which is, in essence, a process of transforming the organizational resource of time into actual sales—allows us to derive important insights into how entrepreneurs can efficiently exploit opportunities. Finally, our study focuses on the market entry of small entrepreneurial firms, so we identify the maximization of short-term sales as a primary objective. We are thus mainly interested in the short-term decisions of entrepreneurs and incumbents, and we focus in particular on tactical levers such as time allocation. As such, we hope that our results will enrich the existing literature on technology entrepreneurship.

Lastly, a fundamental question in entrepreneurship is: why are some entrepreneurs successful and others not [61]? While there exist many explanations attributing entrepreneurial success to the entrepreneur's psychological, social, and educational backgrounds, among other factors, we provide a different rationale based on *tactical-level decisions* made by entrepreneurs. Other tactical-level decisions based on time allocation such as developing supplier relations or investor relations may be fruitful directions for future research.

The simplicity of our model necessarily involves some limitations. First, our model is stylized with the market consisting of two buyers. A fruitful extension would be to accommodate more general consumer network structures, for example, the complete network assumed by [11]. We also do not model the possibility of consumers obtaining information from different channels, e.g. third party reviews. Furthermore, the model incorporates neither cognitive decision "inertia" nor organisational hurdles—each of which could, in practice, affect a purchase decision. Finally, we only consider the entrepreneur's competition with the incumbent but not the case of multiple entrepreneurs competing amongst themselves. It would be worthwhile to examine how the insights of this paper would change as these assumptions are relaxed, which we leave for future research.

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APPENDIX

Proof of Proposition 1: Taking the first derivative of Eq. (1) with respect to n_1 yields the first-order condition (FOC)—namely, Eq. (2). It is easy to verify that the left-hand side (LHS) of Eq. (2) decreases in n_1 and that the RHS of Eq. (2) increases in n_1. Hence there exists a unique solution, n_1^*. □

Proof of Proposition 2: Taking the first derivative of Eq. (3) with respect to n_1 yields the FOC, which is Eq. (4). Recall that the LHS of Eq. (4) contains the hazard function of the standard normal distribution, a function that is increasing in its argument. Now taking the first derivative of the LHS with respect to $\Delta\sqrt{n_1}$, we obtain the term

$$\Delta^2 \cdot \frac{1}{\Delta\sqrt{n_1}} \cdot \frac{\Phi'(\Delta\sqrt{n_1})}{1-\Phi(\Delta\sqrt{n_1})} \cdot [\frac{\Phi'(\Delta\sqrt{n_1})}{1-\Phi(\Delta\sqrt{n_1})} - (\Delta\sqrt{n_1} + \frac{1}{\Delta\sqrt{n_1}})]$$

as well as the inequality

$$\frac{\Phi'(\Delta\sqrt{n_1})}{1-\Phi(\Delta\sqrt{n_1})}-(\Delta\sqrt{n_1}+\frac{1}{\Delta\sqrt{n_1}})<0. \tag{A.1}$$

Inequality (A.1) can be proved as follows. The first derivative of its LHS with respect to $\Delta\sqrt{n_1}$ is

$$\frac{\Phi'(\Delta\sqrt{n_1})}{1-\Phi(\Delta\sqrt{n_1})}\cdot(\frac{\Phi'(\Delta\sqrt{n_1})}{1-\Phi(\Delta\sqrt{n_1})}-\Delta\sqrt{n_1})-1+\frac{1}{(\Delta\sqrt{n_1})^2}>0$$

and, according to Assumption 1(i), $0\le\Delta\sqrt{n_1}\le 1$. Hence the maximum of that derivative is achieved when $\Delta\sqrt{n_1}=1$, and this maximum is negative: $\frac{\Phi'(1)}{1-\Phi(1)}-(1+\frac{1}{1})<0$. So (A.1) holds. The LHS of Eq. (4) is therefore decreasing in $\Delta\sqrt{n_1}$, thus also decreasing in n_1.

Similarly, we take the first derivative with respect to $\Delta\sqrt{N-n_1}$ for the RHS of Eq. (4) and then follow the same steps to show that this RHS is decreasing in $\Delta\sqrt{N-n_1}$ and hence increasing in n_1. We conclude that there must exist a unique solution, n_1^{*L}, to Eq. (4).

Next, we reformulate Eq. (4) as follows:

$$\frac{\Phi'(\Delta\sqrt{n_1})}{\sqrt{n_1}}=\frac{\Phi'(\Delta\sqrt{N-n_1})}{\sqrt{N-n_1}}\cdot\frac{1-\Phi(\Delta\sqrt{n_1})}{R_1/R_2+\Phi(\Delta\sqrt{N})-\Phi(\Delta\sqrt{N-n_1})}.$$

Now dividing both sides of Eq. (2) by R_1 yields

$$\frac{\Phi'(\Delta\sqrt{n_1})}{\sqrt{n_1}}=\frac{\Phi'(\Delta\sqrt{N-n_1})}{\sqrt{N-n_1}}\frac{R_2}{R_1}.$$

Comparing the FOCs that we derived for cases of learning, Eq.(4) and no learning, Eq.(2) reveals that

$$(\frac{R_1}{R_2}+\Phi(\Delta\sqrt{N})-\Phi(\Delta\sqrt{N-n_1}))\cdot\frac{R_2}{R_1}=1+\frac{R_2}{R_1}\cdot(\Phi(\Delta\sqrt{N})-\Phi(\Delta\sqrt{N-n_1}))\ge 1\ge 1-\Phi(\Delta\sqrt{n_1}).$$

Therefore, $\frac{1-\Phi(\Delta\sqrt{n_1})}{R_1/R_2+\Phi(\Delta\sqrt{N})-\Phi(\Delta\sqrt{N-n_1})} \le \frac{R_2}{R_1}$. Thus the RHS of Eq. (4) is always smaller than that of Eq. (2), from which it follows that $n_1^{*\mathrm{L}} \ge n_1^*$. □

Proof of Lemma 1: To prove this lemma, we first start with the following lemma:

Lemma A.1. *The incumbent firm's expected revenue is convex in* k_1.

Proof of Lemma A.1: This lemma is a special case of Lemma A.2, whose proof is given in the proof of Lemma 2. □

Lemma A.1 shows that the maximum revenue is achieved either at $k_1 = K$ or $k_1 = 0$. If the incumbent puts $k_1 = K$, then its expected revenue is $E\pi_{\mathrm{I}}(k_1 = K) = R_1 \cdot \Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{n_1}) + R_2 \cdot \Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{N-n_1})$; for $k_1 = 0$, the expected revenue becomes $E\pi_{\mathrm{I}}(k_1 = 0) = R_1 \cdot \Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{n_1}) + R_2 \cdot \Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{N-n_1})$. Solving for R_1/R_2 such that $E\pi_{\mathrm{I}}(k_1 = K) = E\pi_{\mathrm{I}}(k_1 = 0)$ gives us the valuation threshold

$$\Upsilon^{\mathrm{R}}(n_1) = \frac{\Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{N-n_1}) - \Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{N-n_1})}{\Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{n_1}) - \Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{n_1})}. \quad \square$$

Proof of Proposition 3: Focusing on the decision variable n_1, Lemma 1 gives the valuation threshold $\Upsilon^{\mathrm{R}}(n_1)$, that determines when the entrepreneur switches from one buyer to the other. In the same way, by considering n_2 as the decision variable instead of n_1, the corresponding $\Upsilon^{\mathrm{R}}(n_2)$ should equal $\Upsilon^{\mathrm{R}}(n_1)$ in equilibrium due to symmetry between the two buyers, namley $\Upsilon^{\mathrm{R}}(n_2) = \Upsilon^{\mathrm{R}}(n_1)$. Note that, by applying Lemma 1,

$$\Upsilon^{R}(n_2)=\frac{\Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{N-n_2})-\Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{N-n_2})}{\Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{n_2})-\Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{n_2})}=\frac{\Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{n_1})-\Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{n_1})}{\Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{N-n_1})-\Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{N-n_1})}=\frac{1}{\Upsilon^{R}(n_1)}.$$

Therefore, in equilibrium, $\Upsilon^{*R}=1$.

Given the incumbent's best strategy k_1^* in Lemma 1, the entrepreneur's optimal time allocation n_1^{*R} can be solved by following the same steps as in Proposition 1. In equilibrium, if the incumbent focuses on Buyer 1 (i.e., $k_1^*=K$, when $R_1/R_2>\Upsilon^{*R}=1$) then we know that—as compared with the base case—$\Delta(k_1)$ decreases and $\Delta(k_2)$ increases. We can therefore use the fact that n_1^* is increasing in $\Delta(\cdot)$ to obtain $n_1^{*R}<n_1^*$. Analogously, if the incumbent focuses on Buyer 2 in the equilibrium and so $k_1^*=0$, we know that $\Delta(k_1)$ increases and $\Delta(k_2)$ decreases relative to the base case; hence $n_1^{*R}>n_1^*$. □

Proof of Lemma 2: To prove this proposition, we first start with the following lemma:

Lemma A.2. *In the presence of consumer peer learning, the incumbent firm's expected revenue $E\pi_{\mathrm{I}}$ is convex in k_1.*

Proof of Lemma A.2: We show that, under Assumption 1, the second derivative of the incumbent's function with respect to k_1 is positive. We start by taking the first derivative of Eq. (6) with respect to k_1, which yields the following FOC:

$$\Phi'(\frac{(\lambda+k_1)-\gamma}{\sigma}\cdot\sqrt{n_1})\cdot\sqrt{n_1}\cdot(\frac{R_1}{R_2}+\Phi(\frac{(\lambda+K-k_1)-\gamma}{\sigma}\cdot\sqrt{N-n_1})-\Phi(\frac{(\lambda+K-k_1)-\gamma}{\sigma}\cdot\sqrt{N}))$$

$$=\sqrt{N}\cdot\Phi'(\frac{(\lambda+K-k_1)-\gamma}{\sigma}\cdot\sqrt{N})-\Phi(\frac{(\lambda+k_1)-\gamma}{\sigma}\cdot\sqrt{n_1})(\sqrt{N}\cdot\Phi'(\frac{(\lambda+K-k_1)-\gamma}{\sigma}\cdot\sqrt{N})-\sqrt{N-n_1}\cdot\Phi'(\frac{(\lambda+K-k_1)-\gamma}{\sigma}\cdot\sqrt{N-n_1}))$$

Next we show that LHS and RHS of this FOC are, respectively, increasing and decreasing in k_1. We first focus on the LHS. Since $K<\gamma-\lambda$ and since $\Phi'(\frac{(\lambda+k_1)-\gamma}{\sigma}\cdot\sqrt{n_1})$ is increasing in k_1, it follows that the LHS is also increasing in k_1 only if

$$\mathrm{A}(k_1) = \Phi(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N - n_1}) - \Phi(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N})$$

is increasing in k_1—that is, only if

$$\frac{\partial \mathrm{A}(k_1)}{\partial k_1} = \frac{1}{\sigma} \cdot (\sqrt{N} \cdot \Phi'(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N}) - \sqrt{N - n_1} \cdot \Phi'(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N - n_1})) > 0,$$

from which it follows that $\dfrac{\Phi'(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N})}{\Phi'(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N - n_1})} \geq \dfrac{\sqrt{N - n_1}}{\sqrt{N}}$.

With regard to the RHS, it is easy to verify that $\Phi'(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N})$ and $-\Phi(\frac{(\lambda + k_1) - \gamma}{\sigma} \cdot \sqrt{n_1})$ are both decreasing in k_1. Therefore, RHS decreases with k_1 only if

$$\mathrm{B}(k_1) = \sqrt{N} \cdot \Phi'(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N}) - \sqrt{N - n_1} \cdot \Phi'(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N - n_1})$$

is decreasing in k_1—that is, only if

$$\begin{aligned}\frac{\partial \mathrm{B}(k_1)}{\partial k_1} &= \frac{1}{\sigma} \cdot ((N - n_1) \cdot \Phi''(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N - n_1}) - N \cdot \Phi''(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N}))\\ &= \frac{\gamma - (\lambda + K - k_1)}{\gamma} \cdot ((N - n_1)^{3/2} \cdot \Phi'(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N - n_1}) - N^{3/2} \cdot \Phi'(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N})) \leq 0\end{aligned}$$

from which it follows that $\dfrac{\Phi'(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N})}{\Phi'(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N - n_1})} \geq \dfrac{(N - n_1)^{3/2}}{N^{3/2}} = (\dfrac{\sqrt{N - n_1}}{\sqrt{N}})^3$.

Therefore, a sufficient condition for a positive second derivative is

$$\frac{\Phi'(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N})}{\Phi'(\frac{(\lambda + K - k_1) - \gamma}{\sigma} \cdot \sqrt{N - n_1})} \geq \frac{\sqrt{N - n_1}}{\sqrt{N}} \Leftrightarrow \exp[-\frac{(\lambda + K - k_1 - \gamma)^2}{2\gamma} \cdot n_1] \geq \frac{\sqrt{N - n_1}}{\sqrt{N}}$$

$$\Leftrightarrow \frac{(\lambda + K - k_1 - \gamma)^2}{\gamma} \leq \ln(\frac{N}{N - n_1}) \cdot \frac{1}{n_1}.$$

The implications hold because $\frac{(\lambda+K-k_1-\gamma)^2}{\gamma} \le \frac{(\gamma-\lambda)^2}{\gamma} \le \frac{1}{N} \le \ln(\frac{N}{N-n_1})\cdot\frac{1}{n_1}$; here the first and second inequalities follow from parts (i) and (ii), respectively, of Assumption 1.□

Lemma A.2 shows that the maximum revenue is achieved either at either $k_1 = K$ or $k_1 = 0$, and its expected revenue under that choice is (respectively):

$$E\pi_1(k_1 = K) = R_1 \cdot \Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{n_1}) + R_2 \cdot \Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{N}) \cdot \Phi(\frac{\gamma-\lambda-K}{\sigma}\cdot\sqrt{n_1})$$
$$+ R_2 \cdot \Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{N-n_1}) \cdot \Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{n_1});$$

$$E\pi_1(k_1 = 0) = R_1 \cdot \Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{n_1}) + R_2 \cdot \Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{N}) \cdot \Phi(\frac{\gamma-\lambda}{\sigma}\cdot\sqrt{n_1})$$
$$+ R_2 \cdot \Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{N-n_1}) \cdot \Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{n_1}).$$

Solving for R_1/R_2 such that $E\pi_{\mathrm{I}}(k_1 = K) = E\pi_{\mathrm{I}}(k_1 = 0)$, we obtain the threshold

$$\Upsilon^{\mathrm{LR}} = \frac{\Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{N})\cdot\Phi(\frac{\gamma-\lambda}{\sigma}\cdot\sqrt{n_1}) + \Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{N-n_1})\cdot\Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{n_1})}{\Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{n_1}) - \Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{n_1})}$$

$$-\frac{\Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{N})\cdot\Phi(\frac{\gamma-\lambda-K}{\sigma}\cdot\sqrt{n_1}) + \Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{N-n_1})\cdot\Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{n_1})}{\Phi(\frac{\lambda+K-\gamma}{\sigma}\cdot\sqrt{n_1}) - \Phi(\frac{\lambda-\gamma}{\sigma}\cdot\sqrt{n_1})}. \qquad \text{(A.2)}$$

Comparing with Case R, in Case LR with consumer peer learning, the effective revenue from Buyer 1,

$$\Re_1 = R_1 + R_2(\Phi(\Delta\sqrt{N}) - \Phi(\Delta\sqrt{N-n_1})) \ge R_1.$$

By replacing R_1 with $\Re_1$, the valuation threshold for $\Re_1/R_2$ is equal to Υ^{R}, therefore, the valuation threshold for R_1/R_2, $\Upsilon^{\mathrm{LR}} < \Upsilon^{\mathrm{R}} = 1$. □

Proof of Proposition 4: Proving part (i) is similar to Proposition 3, thus is omitted here. For part (ii), we know from Proposition 2 that, given a fixed k_i, the entrepreneur always allocates more time to Buyer 1 in the presence of consumer peer learning. So unless the incumbent changes its focus, the entrepreneur focuses on Buyer 1 when there is consumer peer learning. As a result, $n_1^{*LR}(k_1=0) > n_1^{*R}(k_1=0)$ and $n_1^{*LR}(k_1=K) > n_1^{*R}(k_1=K)$, when $R_1/R_2 < \Upsilon^{LR}$ or $R_1/R_2 > 1$. □

REFERENCES

[1] M. Song, K. Podoynitsyna, H. Van Der Bij, and J. I. Halman, "Success factors in new ventures: A meta‐analysis," *Journal of Product Innovation Management,* vol. 25, no. 1, pp. 7-27, 2008.

[2] W. Deutsch and C. Wortmann, "Entrepreneurial selling," *Chicago, IL: Polsky Center for Entrepreneurship,* 2011.

[3] A. R. Reuber and E. M. Fischer, "Entrepreneurs' experience, expertise, and the performance of technology-based firms," *IEEE Transactions on Engineering Management,* vol. 41, no. 4, pp. 365-374, 1994.

[4] J. S. Gans and S. Stern, "The product market and the market for "ideas": commercialization strategies for technology entrepreneurs," *Research Policy,* vol. 32, no. 2, pp. 333-350, 2003.

[5] K. E. Klein, "Great product. Now, how to sell it?," *Bloomberg Business Week,* March 15 2012.

[6] J. W. Carland, F. Hoy, W. R. Boulton, and J. A. C. Carland, "Differentiating entrepreneurs from small business owners: A conceptualization," *Academy of Management Review,* vol. 9, no. 2, pp. 354-359, 1984.

[7] S. Mueller, T. Volery, and B. Von Siemens, "What do entrepreneurs actually do? An observational study of entrepreneurs' everyday behavior in the start‐up and growth stages," *Entrepreneurship Theory and Practice,* vol. 36, no. 5, pp. 995-1017, 2012.

[8] N. Joglekar and M. Lévesque, "The role of operations management across the entrepreneurial value chain," *Production and Operations Management,* vol. 22, no. 6, pp. 1321-1335, 2013.

[9] S. H. Hanks and G. Chandler, "Patterns of functional specialization in emerging high tech firms," *Journal of Small Business Management,* vol. 32, no. 2, p. 23, 1994.

[10] S. Bikhchandani, D. Hirshleifer, and I. Welch, "Learning from the behavior of others: Conformity, fads, and informational cascades," *The Journal of Economic Perspectives,* vol. 12, no. 3, pp. 151-170, 1998.

[11] A. Banerjee and D. Fudenberg, "Word-of-mouth learning," *Games and Economic Behavior,* vol. 46, no. 1, pp. 1-22, 1// 2004.

[12] J. A. Chevalier and D. Mayzlin, "The effect of word of mouth on sales: Online book reviews," *Journal of Marketing Research,* vol. 43, no. 3, pp. 345-354, 2006.

[13] F. Deroïan, "Formation of social networks and diffusion of innovations," *Research Policy,* vol. 31, no. 5, pp. 835-846, 2002.

[14] G. Ellison and D. Fudenberg, "Word-of-mouth communication and social learning," *The Quarterly Journal of Economics,* pp. 93-125, 1995.

[15] H. P. Young, "Innovation diffusion in heterogeneous populations: Contagion, social influence, and social learning," *The American Economic Review,* vol. 99, no. 5, pp. 1899-1924, 2009.

[16] J. R. Hauser and S. M. Shugan, "Defensive marketing strategies," *Marketing Science,* vol. 27, no. 1, pp. 88-110, 2008.

[17] K. Aboulnasr, O. Narasimhan, E. Blair, and R. Chandy, "Competitive response to radical product innovations," *Journal of Marketing,* vol. 72, no. 3, pp. 94-110, 2008.

[18] A. Burke and A. van Stel, "Entry and exit in disequilibrium," *Journal of Business Venturing,* vol. 29, no. 1, pp. 174-192, 2014.

[19] Y. V. Joshi, D. J. Reibstein, and Z. J. Zhang, "Optimal entry timing in markets with social influence," *Management Science,* vol. 55, no. 6, pp. 926-939, 2009.

[20] R. Wang and Q. Wen, "Strategic invasion in markets with switching costs," *Journal of Economics & Management Strategy,* vol. 7, no. 4, pp. 521-549, 1998.

[21] S. Gifford, "Allocation of entrepreneurial attention," *Journal of Economic Behavior & Organization,* vol. 19, no. 3, pp. 265-284, 1992.

[22] O. S. Yoo, C. J. Corbett, and G. Roels, "Optimal time allocation for process improvement for growth-focused entrepreneurs," *Manufacturing & Service Operations Management,* vol. 18, no. 3, pp. 361-375, 2016.

[23] O. S. Yoo, G. Roels, and C. J. Corbett, "The Time–Money Trade-Off for Entrepreneurs: When to Hire the First Employee?," *Manufacturing & Service Operations Management,* vol. 18, no. 4, pp. 559-569, 2016.

[24] A. M. McCarthy, D. Krueger, and T. Schoenecker, "Changes in the time allocation patterns of entrepreneurs," *Entrepreneurship Theory and Practice,* vol. 15, no. 2, pp. 7-18, 1990.

[25] G. S. Becker, "A theory of the allocation of Time," *The Economic Journal,* pp. 493-517, 1965.

[26] R. Radner and M. Rothschild, "On the allocation of effort," *Journal of Economic Theory*, vol. 10, no. 3, pp. 358-376, 1975.
[27] M. Levesque, D. A. Shepherd, and E. J. Douglas, "Employment or self-employment: A dynamic utility-maximizing model," *Journal of Business Venturing*, vol. 17, no. 3, pp. 189-210, 2002.
[28] A. Cooper, M. Ramachandran, and D. Schoorman, "Time allocation patterns of craftsmen and administrative entrepreneurs: Implications for financial performance," *Entrepreneurship: Theory and Practice*, vol. 22, no. 2, pp. 123-124, 1997.
[29] M. Lévesque and C. Schade, "Intuitive optimizing: Experimental findings on time allocation decisions with newly formed ventures," *Journal of Business Venturing*, vol. 20, no. 3, pp. 313-342, 2005.
[30] K. Burmeister-Lamp, M. Lévesque, and C. Schade, "Are entrepreneurs influenced by risk attitude, regulatory focus or both? An experiment on entrepreneurs' time allocation," *Journal of Business Venturing*, vol. 27, no. 4, pp. 456-476, 2012.
[31] J. Lee, J. Lee, and H. Lee, "Exploration and exploitation in the presence of network externalities," *Management Science*, vol. 49, no. 4, pp. 553-570, 2003.
[32] B. Jing, "Social learning and dynamic pricing of durable goods," *Marketing Science*, vol. 30, no. 5, pp. 851-865, 2011.
[33] M. Yu, L. Debo, and R. Kapuscinski, "Strategic waiting for consumer-generated quality information: Dynamic pricing of new experience goods," *Management Science*, vol. 62, no. 2, pp. 410-435, 2015.
[34] T. Liu and P. Schiraldi, "New product launch: Herd seeking or herd preventing?," *Economic Theory*, vol. 51, no. 3, pp. 627-648, 2012.
[35] M.-J. Chen and D. Miller, "Competitive attack, retaliation and performance: An expectancy-valence framework," *Strategic Management Journal*, vol. 15, no. 2, pp. 85-102, 1994.
[36] D. Bowman and H. Gatignon, "Determinants of competitor response time to a new product introduction," *Journal of Marketing Research*, pp. 42-53, 1995.
[37] V. Shankar, "New product introduction and incumbent response strategies: Their interrelationship and the role of multimarket contact," *Journal of Marketing Research*, pp. 327-344, 1999.
[38] T. S. Robertson, J. Eliashberg, and T. Rymon, "New product announcement signals and incumbent reactions," *The Journal of Marketing*, pp. 1-15, 1995.
[39] A. Kalra, S. Rajiv, and K. Srinivasan, "Response to competitive entry: A rationale for delayed defensive reaction," *Marketing Science*, vol. 17, no. 4, pp. 380-405, 1998.
[40] S. Kuester, C. Homburg, and T. S. Robertson, "Retaliatory behavior to new product entry," *The Journal of Marketing*, pp. 90-106, 1999.
[41] R. Katila, E. L. Chen, and H. Piezunka, "All the right moves: How entrepreneurial firms compete effectively," *Strategic Entrepreneurship Journal*, vol. 6, no. 2, pp. 116-132, 2012.
[42] R. Katila and P. Y. Mang, "Exploiting technological opportunities: the timing of collaborations," *Research Policy*, vol. 32, no. 2, pp. 317-332, 2003.
[43] N. R. Joglekar and M. Levesque, "Marketing, R&D, and startup valuation," *IEEE Transactions on Engineering Management*, vol. 56, no. 2, pp. 229-242, 2009.
[44] B. Wu and A. M. Knott, "Entrepreneurial risk and market entry," *Management Science*, vol. 52, no. 9, pp. 1315-1330, 2006.
[45] E. G. Anderson and G. G. Parker, "Integration and cospecialization of emerging complementary technologies by startups," *Production and Operations Management*, vol. 22, no. 6, pp. 1356-1373, 2013.
[46] C. E. Helfat and M. B. Lieberman, "The birth of capabilities: market entry and the importance of pre‐history," *Industrial and Corporate Change*, vol. 11, no. 4, pp. 725-760, 2002.
[47] E. Ofek, Z. Katona, and M. Sarvary, "“Bricks and clicks”: The impact of product returns on the strategies of multichannel retailers," *Marketing Science*, vol. 30, no. 1, pp. 42-60, 2011.
[48] B. McWilliams, "Money-back guarantees: Helping the low-quality retailer," *Management Science*, vol. 58, no. 8, pp. 1521-1524, 2012.
[49] S. Morris and H. S. Shin, "Social value of public information," *The American Economic Review*, vol. 92, no. 5, pp. 1521-1534, 2002.
[50] N. C. Petruzzi and M. Dada, "Pricing and the newsvendor problem: A review with extensions," *Operations Research*, vol. 47, no. 2, pp. 183-194, 1999.
[51] W. J. Ferrier, K. G. Smith, and C. M. Grimm, "The role of competitive action in market share erosion and industry dethronement: A study of industry leaders and challengers," *Academy of management journal*, vol. 42, no. 4, pp. 372-388, 1999.
[52] V. Rindova, W. J. Ferrier, and R. Wiltbank, "Value from gestalt: how sequences of competitive actions create advantage for firms in nascent markets," *Strategic Management Journal*, vol. 31, no. 13, pp. 1474-1497, 2010.
[53] D. miller and J.-M. Toulouse, "Strategy, structure, CEO personality and performance in small firms," *American Journal of Small Business*, vol. 10, no. 3, pp. 47-62, 1986.
[54] A. M. Rugman and A. Verbeke, "Does competitive strategy work for small business?," *Journal of Small Business & Entrepreneurship*, vol. 5, no. 3, pp. 45-50, 1988.

[55] N. M. Carter, T. M. Stearns, P. D. Reynolds, and B. A. Miller, "New venture strategies: Theory development with an empirical base," *Strategic Management Journal*, vol. 15, no. 1, pp. 21-41, 1994.

[56] R. Katila and S. Shane, "When does lack of resources make new firms innovative?," *Academy of Management Journal*, vol. 48, no. 5, pp. 814-829, 2005.

[57] H. S. Nair, P. Manchanda, and T. Bhatia, "Asymmetric social interactions in physician prescription behavior: The role of opinion leaders," *Journal of Marketing Research*, vol. 47, no. 5, pp. 883-895, 2010.

[58] M. Trusov, A. V. Bodapati, and R. E. Bucklin, "Determining influential users in internet social networks," *Journal of Marketing Research*, vol. 47, no. 4, pp. 643-658, 2010.

[59] M. Lévesque, "Mathematics, theory, and entrepreneurship," *Journal of Business Venturing*, vol. 19, no. 5, pp. 743-765, 2004.

[60] D. A. Shepherd and H. Patzelt, "Operational entrepreneurship: How operations management research can advance entrepreneurship," *Production and Operations Management*, vol. 22, no. 6, pp. 1416-1422, 2013.

[61] S. Venkataraman, "The distinctive domain of entrepreneurship research," *Advances in Entrepreneurship, Firm emergence and Growth*, vol. 3, no. 1, pp. 119-138, 1997.

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