

Innovation Diffusion among Case-based Decision-makers^{*}

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Abstract

This paper analyzes a model of innovation diffusion with case-based individuals a la [Gilboa and Schmeidler \(1995, 1996, 1997\)](#), who decide whether to consume an incumbent or a new product based on their and their social neighbors' previous consumption experiences. I analyze how diffusion patterns change with individual characteristics, innovation characteristics, and social networks. In particular, information about a superior innovation could be overwhelmed by information about the incumbent product, leading to inefficient asymptotic diffusion. Radical innovation or innovation with a strong R&D focus leads to higher initial speed but lower acceleration than incremental innovation or innovation with strong marketing effort. Social networks with stronger overall social ties, lower degrees of homophily, or higher exposure to reviews from early adopters speed up the diffusion of innovation.

Keywords: Innovation diffusion, case-based decision theory, radical innovation, incremental innovation, satisficing, social network

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1 Introduction

Understanding how innovations diffuse among consumers/producers is crucial to technological adoption in society and the incentive for firms to innovate. A low rate of adoption leads to forgone benefits in economic development and environmental improvement (see [Kemp and Volpi \(2008\)](#), [Jack \(2013\)](#)). Even when an innovation is significantly better than existing products, consumers/producers may fail to adopt it due to uncertainty, inertia, and other reasons (see [Stoneman and Diederer \(1994\)](#), [Henard and Szymanski \(2001\)](#)). This paper aims to understand the diffusion patterns of new products with a simple yet rich micro-founded model. In particular, I will discuss how individual characteristics, the nature of the innovation, and social networks affect both short-term and long-term diffusion patterns.

An important building block of this paper is the case-based decision theory (hereinafter CBDT) by [Gilboa and Schmeidler \(1995, 1996, 1997\)](#) (hereinafter GS), which I use to model adoption decisions. Roughly speaking, before making their purchasing decisions, individuals collect cases of consumption experiences with different products from their memories, friends, family, and social network. They then normalize these experiences using their aspiration levels, corresponding to their tendency for satisficing behavior ([Simon \(1956\)](#)). In the last step, they aggregate the information and compute their evaluation of different products using a weighted sum of these experiences.

Compared to existing models (e.g., Bayesian or contagion models), CBDT captures important and more realistic elements of adoption decisions and, as shown later, drives additional and sometimes contrasting policy and managerial implications. First, CBDT assumes no knowledge requirement for individuals. Imagine an individual observes some consumption experiences of innovation from his close friends. In a Bayesian model, to use this information, the individual must understand what drives his close friends' consumption experiences, their decisions to adopt (or not to adopt) the innovation, and information about the close friends of their close friends, etc. They also must have prior knowledge about the quality and characteristics of the innovation. Possession of such knowledge is unrealistic, especially in settings with novel innovations and a large population of heterogeneous individuals. In contrast, in CBDT, individuals have no prior knowledge about their own and others' payoff and innovation characteristics.

Second, case-based individuals tend to satisfice, which is a widely documented and studied behavior in the psychology and marketing literature ([Simon \(1956\)](#); [Jacoby et al. \(1978\)](#); [Chowdhury et al. \(2009\)](#); [Caplin et al. \(2011\)](#); [Roets et al. \(2012\)](#); [Misuraca et al. \(2015\)](#)). In particular, [Jacoby et al. \(1978\)](#) shows that

satisficing behavior is especially prominent when consumers do not have much previous purchasing experiences, suggesting it is an important consideration when it comes to innovation adoption. In other words, consumers tend to stick to options that are good enough, which limits innovation diffusion. Despite the importance of satisfying behaviors, existing studies have overlooked their linkage to innovation adoption. As will be shown in the main text, consumers' (heterogeneous) tendency to satisfice drives a number of important and novel results compared to the existing literature.

Lastly, the model is simple yet rich enough to allow discussion on how heterogeneous individual and innovation characteristics affect adoption. More specifically, using the CBDT, this paper analyzes how innovation diffusion depends on the heterogeneous tendencies to satisfice, characteristics of the social network, quality of the incumbent and new products, product designs, and marketing strategies.

I consider a discrete, infinite-time model with an incumbent product and a new product. Individuals start with the incumbent product in the first period, then in all later periods, decide whether to consume the incumbent or the new product. After payoffs are realized in each period, individuals update their evaluations of the two products based on everyone's consumption experiences, according to CBDT. I focus on the more interesting case where the new product is superior to the incumbent product, i.e., it yields a higher payoff for everyone.

The first set of results in this paper characterizes the adoption process. First, I show that if an individual consumes the new product in period t , he also consumes the new product for all $t' \geq t$. This result simplifies the characterization of the adoption process as the set of individuals who adopt the new product weakly increases in t . Next, the heterogeneous tendency to satisfice plays a big role in innovation diffusion. Individuals with less tendency to satisfice adopt the new product in earlier periods because they are more willing to experiment, as shown in GS. The experiences of these early adopters then create a novel spillover effect compared to the single-agent setting in GS: individuals with a higher tendency to satisfice, who will never adopt the new product in a single-agent setting, may adopt the new product after observing early adopters' consumption experiences. Using the terminologies in [Rogers \(2010\)](#), innovators and early adopters are more willing to experiment as they hunt for high-quality products, while the late majority and laggards wait and adopt the innovation only if they observe sufficient good reviews from others.

Second, some individuals might never consume the superior new product, which leads to asymptotic inefficiency. This happens when the social network is too sparse, individuals are too heterogeneous in taste, they have high tendencies to satisfice, the

innovation is only marginally superior, or when the innovation is too dissimilar to the incumbent product. In contrast with the existing literature, an inefficient level of adoption happens even when there are infinite cases of good experiences with the new product. This is driven by individuals' tendencies to satisfice. Roughly speaking, a decent incumbent product with many reviews is better than a superior product with fewer reviews. It thus suggests that an information campaign promoting innovation could be ineffective if it is overwhelmed by the many experiences with the incumbent product, which is more likely to be true if the incumbent product is established or has a huge following.

Next, I analyze how product characteristics affect the adoption process. More specifically, I compare the diffusion properties of radical versus incremental innovation. I show that radical innovation diffuses with a higher initial speed but lower acceleration than incremental innovation. The result is driven by the fact that individuals with different tendencies to satisfice adopt the new product in different periods during the diffusion process. More specifically, radical innovation sells better among individuals who have lower tendencies to satisfice and adopt the innovation in earlier periods, as they care more about the quality of the innovation. In contrast, in later periods, radical innovation struggles to maintain momentum with individuals with higher tendencies to satisfy, as they care more about the quantity of consumption experiences they see. Similarly, an innovation with higher R&D spending would sell better in the early periods than an innovation with high marketing spending, but the latter is better at gaining momentum and may diffuse to a larger market eventually. This result has welfare implications in relation to the discount factor and the positioning of the new firm. Given two innovations with the same asymptotic level of adoption, an impatient social planner/firm with a low discount factor would prefer radical innovation with a higher initial speed of diffusion than incremental innovation with a higher acceleration of diffusion. Similarly, a product with high R&D expenditure is better positioned as a niche product for the enthusiasts, while a product with high marketing expenditure could more successfully diffuse to the general public.

Lastly, I analyze two simple examples to illustrate how social networks affect product diffusion. First, homophily slows down innovation adoption. Second, uniformly increased connectivity in the network speeds up diffusion. In contrast, diffusion is slower if the network ties with individuals with higher tendencies to satisfice, i.e., later adopters, are stronger, and is faster if individuals are more connected with individuals with lower tendencies to satisfice. It implies that platform strategies that highlight reviews from consumers who experiment more can speed up adoption

and encourage innovation.

The paper is outlined as follows. I discuss the related literature and the contribution of this paper in the next section. In Section 3, I introduce the model setup. In Section 4, I show that diffusion patterns are characterized by a decreasing sequence of aspiration thresholds. Section 5 compares the diffusion patterns with different innovation characteristics. Section 6 presents results on how social network affects diffusion. In Section 7, I discuss managerial and marketing implications and connect the theoretical results to business cases. Lastly, I conclude.

2 Related Literature

This paper relates to the literature on innovation diffusion (e.g., [Jensen \(1982\)](#)). Existing studies have also shown that there can be an asymptotically inefficient level of adoption, even when the innovation is superior. For example, in [Chatterjee and Eliashberg \(1990\)](#) and [Campbell \(2013\)](#), some individuals might never adopt an innovation because it is too expensive; in [Chatterjee and Xu \(2004\)](#), full adoption might not happen due to conformism; in [Frick and Ishii \(2024\)](#) and [Board and Meyer-ter Vehn \(2021\)](#) where signals arrive in Poisson process, adoption might come to a standstill as consumers grow pessimistic in the absence of good signals; lastly, insufficient private motivation to experiment precludes adoption of innovation in herding models ([Banerjee \(1992\)](#); [Bikhchandani et al. \(1992\)](#); [Smith and Sørensen \(2000\)](#)).

In contrast, this paper proposes a novel mechanism for inefficient asymptotic adoption. One important distinction is that inefficient adoption happens not because of the absence of information, but because information about the innovation is overwhelmed by the information about the incumbent product. Thus, even if some consumers keep consuming the innovation and share their good experience, individuals with a high tendency to satisfy might not adopt the superior innovation. Unlike the models mentioned in the previous paragraph, it implies that even if a social planner/firm keeps conveying good information about the innovation, inefficient adoption could still exist.

Moreover, the result comparing radical and incremental innovation links two key concepts of diffusion curves (initial speed and acceleration) with innovation characteristics. Initial speed and acceleration are two important parameters used in macro-diffusion models, such as [Bass \(1969\)](#), [Horsky and Simon \(1983\)](#), and [Bass et al. \(1994\)](#), which characterize diffusion patterns using reduced-form differential equations. This paper, therefore, provides a micro-foundation on how the two pa-

rameters are affected by product characteristics. The result also contrasts with contagion models (e.g., [Jackson and Yariv \(2006\)](#), [Campbell \(2013\)](#), and [Board and Meyer-ter Vehn \(2021\)](#)) in which a larger population of early adopters also increases acceleration.

3 Model Setup

Consider a market where N individuals, indexed by i , decide whether to consume one of two products. One of the two products is an established incumbent product, denoted as p_c , and the other is a new product, denoted as p_n . Time is discrete and runs from $t = 0, 1, 2, \dots$. In period $t = 0$, only p_c is available; thus, all individuals consume the incumbent product. In each period $t = 1, 2, \dots$, individuals decide whether to consume p_c or p_n ; thus, switching to the new product is reversible. We denote the set of individuals who consume p_c and p_n in period t as D_c^t and D_n^t , which, with some abuse of notation, also denote the number of individuals who consume the two products in period t . Obviously, $D_c^t \cap D_n^t = \emptyset$ and $D_c^t \cup D_n^t = \{1, 2, \dots, N\}$ for all t , and by assumption $D_n^0 = \emptyset$. In the following, we analyze how the demand for the incumbent and new product, i.e., D_c^t and D_n^t , evolves over time.

Payoffs In each period, consuming the incumbent product yields a payoff v_L , and consuming the new product yields a payoff $v_H > v_L$. Thus, payoffs from the incumbent and the new products are deterministic, while the new product is superior. However, individuals do not know v_L and v_H or that the payoffs are deterministic. Instead, they form evaluations of the two products using cases of consumption experiences, as will be introduced later in this Section. Note that the assumption of deterministic payoffs approximates stochastic payoffs with a large population, where v_H and v_L are the average payoffs from the new and incumbent products, respectively. I will discuss how an inferior new product changes the diffusion pattern at the end of Section 5.

Cases Each individual i is endowed with cases C_t in period t , in which its elements are tuple $(j, p, v) \in \{1, \dots, N\} \times \{p_c, p_n\} \times \mathbb{R}$. Each case (j, p, v) is a review or a consumption experience, which says an individual j consumed a product p and got payoff v . For example, a consumer might hear from her friend about her experience with a new smartphone or see a detailed report on a review website about the same phone. The consumer then uses these experiences to evaluate the old and new products, and makes her purchasing decisions accordingly, as discussed later in this

Section.

In period 0, individuals start with no cases, i.e., $C_0 = \emptyset$. From period 1 onward, individuals incorporate everyone's consumption experiences into their cases.¹ Formally, cases in period t is constructed using the following recursive formula: $C_t = C_{t-1} \cup \{(j, p_c, v_L) : j \in D_c^{t-1}\} \cup \{(j, p_n, v_H) : j \in D_n^{t-1}\}$.

Product Evaluations Following GS, given cases C_t , a product p is evaluated with the following U function:

$$U_i^t(p) = \sum_{(j, p', v) \in C_t} s_{i,j} s_{p,p'} (v - H_i). \quad (1)$$

I call $U_i^t(p)$ the individual i 's evaluation of product p given cases C_t , or sometimes simply the evaluation of product p . Individuals consume the new product if and only if its evaluation is higher than that of the incumbent product, i.e., $U_i^t(p_n) > U_i^t(p_c)$.

Using the terminologies in GS, $s_{i,j}$ and $s_{p,p'}$ are the similarity parameters between individuals and products, respectively, and H_i is the aspiration levels of individual i . The similarity parameters $s_{i,j}$ and $s_{p,p'}$ determine how fast the evaluation changes with each case and, as will be discussed later in this Section, capture different characteristics of the products, consumers, and social network. The aspiration level H_i determines whether an experience is good enough (whether $v > H_i$) and characterizes the individual's tendency to satisfice. Note that when $v > H_i$, the experience is considered "good enough" for individual i , and it enhances the evaluation of the product; when $v < H_i$, the experience is considered a bad experience, and it decreases the evaluation of the product. Equation (1) could be interpreted as follows: in period t individuals collect a database of consumption experience C_t from their previous selves and others, from reviews on platforms or in-person interactions, and then aggregate different individuals' consumption experiences with different products using the weights $s_{i,j} s_{p,p'}$ while normalizing the experiences using their aspiration level H_i . Note that, unlike Bayes' formula, Equation (1) does not require individuals to know the structures of their and others' payoffs and others' decision-making processes. Assuming consumers have such knowledge is particularly unrealistic in a model of new product diffusion or with many consumers.

Individuals have heterogeneous aspiration levels, denoted as $H_i \in \mathbb{R}$, which they use to evaluate the two products. As discussed in the introduction, lower aspiration

¹Note that it is without loss of generality to assume individuals incorporate everyone's consumption experiences into their cases. For example, inattention to others' experiences because of weak social ties or limited cognition could be captured through the similarity parameter introduced later in this Section.

levels correspond to a higher tendency of satisficing behavior, akin to the reservation utility in [Caplin et al. \(2011\)](#). As evidenced in [Jacoby et al. \(1978\)](#), consumers tend to satisfice when they have limited knowledge of the products. Thus, the aspiration level captures an important feature in consumers' decision-making process, which is absent from the Bayesian model. Without loss of generality, I assume that there are $G \leq N$ mutually exclusive groups of individuals with different aspiration levels, with $N_1, N_2, \dots, N_G$ denoting the set itself and also its cardinality. H_i differs only across group such that $H_i = H_j$ if and only if $i, j \in N_k$ for some $k = 1, \dots, G$. With some abuse of notations, I also denote the aspiration levels of individuals in a group N_k as H_{N_k} . Without loss of generality, I order the aspiration levels such that H_{N_k} is strictly decreasing in k . I assume that $H_{N_1} \in (v_L, v_H]$, such that at least some individuals aspire to a higher payoff than what the incumbent product offers. It ensures that the adoption dynamic is non-trivial and that at least some individuals adopt the new product at some period. Without loss of generality, I assume that $H_{N_2} < v_L$ such that only group N_1 aspire a higher payoff than v_L .²

In the baseline model, for simplicity, I assume that the similarity parameters between individuals follow (this assumption will be relaxed in [Section 6](#)):

$$s_{i,j} = \begin{cases} s \in [0, 1] & \text{if } i \neq j; \\ 1 & \text{if } i = j. \end{cases} \quad (2)$$

Equation (2) and the assumption that $s \leq 1$ imply that individuals discount consumption experiences from others. Note that $s_{i,j}$ could be interpreted as a weighted and directed network among the N individuals. In this case, Equation (2) implies that the social network among the N individuals is a symmetric and complete network where the strength of cross-individual ties is s and the strength of self-connections is 1. Depending on the interpretation, the parameter s measures individuals' diversity or the social network's sparsity. When individuals are more diverse such that others' experiences are less informative, or when individuals' network ties are weaker, s becomes smaller, and the experiences of others have a smaller influence on one's evaluation of the product. s also measures how easy it is to read/access others' consumption experiences. For example, with social media and technology advances, it is easier to share and search for product reviews; hence, s increases.

²Note that the assumption that $H_{N_2} < v_L$ induces no loss of generality as $H \geq v_L$ does not affect the diffusion pattern.

For the product similarity parameters, we assume

$$\begin{aligned} s_{p_n, p_n} &> s_{p_c, p_n}; \\ s_{p_c, p_c} &> s_{p_n, p_c}. \end{aligned} \tag{3}$$

The first inequality $s_{p_n, p_n} > s_{p_c, p_n}$ ensures that experiences of the new product have a larger impact on its evaluation than that of the incumbent product; similarly, the second inequality $s_{p_c, p_c} > s_{p_n, p_c}$ ensures that experiences of the incumbent product have a larger impact on its evaluation than that of the new product.

I also define

$$s_p \equiv \frac{s_{p_n, p_n} - s_{p_c, p_n}}{s_{p_c, p_c} - s_{p_n, p_c}}.$$

Note that a good experience of the new product increases its evaluation relative to the incumbent product's evaluation in proportional to the numerator $s_{p_n, p_n} - s_{p_c, p_n}$, while a good experience of the incumbent product increases its evaluation relative to the new product's evaluation in proportional to the denominator $s_{p_c, p_c} - s_{p_n, p_c}$. Thus, roughly speaking, the ratio s_p represents the “learning speed” towards the new product relative to the incumbent product. Fixing other model parameters and given $v_H > H_i$, the higher s_p is, the faster the new product's evaluation increases relative to the incumbent product's.

The parameters v_H , v_L , and s_p capture both product designs and marketing strategies. Thus, analyzing how these three parameters affect diffusion patterns yields a wide range of important managerial and marketing insights despite the model's simplicity. First, v_H and v_L represent the quality of the new and the incumbent product, and are affected by firms' technological advantages and R&D expenses. On the other hand, s_p captures how consumers internalize the experiences of the new and incumbent products. Both product designs and marketing strategies could drive a higher s_p . For example, a niche design will likely generate experiences with higher variance; thus, a good experience with the new product would not change its evaluation much. Similarly, if the new product is not user-friendly, each consumption would yield different experiences depending on how well individuals use the product, which implies a lower s_p (or a lower s_{p_n, p_n}). Last but not least, increasing marketing expenditure could increase s_p by educating consumers to appreciate the new product's novel and superior features. Section 5 will analyze how the trade-off between v_H and s_p , potentially driven by the trade-off between R&D and marketing expenses, affects diffusion patterns.

4 Adoption Dynamics

In this section, I present the diffusion dynamics, i.e., the individuals' consumption in each period, given product specifications (v_L, v_H, s_p) and individual characteristics s and $H_{N_1}, \dots, H_{N_G}$. The following Lemma shows that although adopting the new product is reversible, individuals do not return to the incumbent product.

Lemma 1. *Once an individual chooses the new product in period t , he chooses the new product in all future periods. Thus, $D_n^{t-1} \subseteq D_n^t$ for all t .*

The proof of Lemma 1 and other results are shown in the Appendix. The Lemma is proved by induction. If an individual i switches from the incumbent product to the new product in period t , it must be that the consumption cases in period $t - 1$ increase the evaluation of the new product more than that of the incumbent product. Next, in period t , as there are more individuals, including i , consuming the new product, the evaluation of the new product must increase even more than the increase in the evaluation of the incumbent product. Therefore, individual i also consumes the new product in period $t + 1$.

The following Proposition further shows that the population of individuals that buy the new product in period t must be a weakly increasing segment of aspiration levels.

Proposition 1. *In each period, only individuals with high enough aspiration levels consume the new product. Individuals with lower aspiration levels either never consume the new product or start consuming it in later periods. Formally, there exists a unique threshold $\underline{H}_t \in \mathbb{R} \cup \{-\infty\}$ such that $D_n^t = \{i : H_i > \underline{H}_t\}$. Moreover, the threshold $\underline{H}_t$ weakly decreases in t .*

The adoption process is thus characterized by a unique sequence of (weakly) decreasing thresholds $\underline{H}_1, \underline{H}_2, \dots$. As in the spirit of GS and existing satisficing models, individuals with higher aspiration levels have less tendency to satisfice, are more inclined to experiment, and thus adopt the new product earlier. Unlike GS and existing satisficing models, the current multi-agent model also gives rise to a novel spillover effect. In a single-agent setting in GS, only individuals in N_1 will adopt the new product as $H_{N_1} > v_L$. Similarly, in a single-agent setting in existing satisficing models, the incumbent product is good enough for individuals in $N_2, \dots, N_G$, i.e., $v_L \geq H_{N_2}, \dots, H_{N_G}$, and thus they never switch to the new product. In contrast, here, even individuals whose aspiration levels are so low that they would stick with the incumbent product in a single-agent setting may eventually switch to the new product because they observe the experiences of individuals with

higher aspiration levels. In other words, individuals benefit from the information from the “experimentation” of others in society.

Lemma 1 and Proposition 1 provide a simple characterization of the diffusion pattern and, importantly, show a link between individuals’ adoption decisions and their tendency to satisfice. It establishes a testable implication and a correspondence between this micro-based diffusion model and the macro-based diffusion model like Rogers (2010): Using measures on tendencies of satisficing (e.g., Misuraca et al. (2015)), individuals can be classified into innovators, early adopters, early majority, late majority, and laggards in an ascending order of tendencies to satisfice/descending order of aspiration levels.

Now, for ease of notation, denote $F(H)$ as the complementary cumulative mass function of aspiration levels, i.e., the mass of individuals with aspiration levels strictly higher than H :

$$F(H) = \sum_{n=1}^k N_n \text{ where } H_{N_{k+1}} \leq H < H_{N_k}.$$

The following Proposition presents the results on the asymptotic market share of the new product.

Proposition 2. *More individuals eventually consume the new product if*

1. *individuals discount others’ experiences less, i.e., s is larger, or;*
2. *the new product is more superior, i.e., v_H is larger, or;*
3. *the learning speed towards the new product relative to the incumbent product is faster, i.e., s_p is larger, or;*
4. *individuals have higher aspiration levels, i.e., H_i increases in the sense of F.O.S.D..*

More specifically, all individuals eventually consume the new product if and only if there does not exist a $H \in [H_{N_G}, H_{N_1})$ such that

$$\frac{v_H - H}{v_L - H} \leq \frac{[s[N - F(H) - 1] + 1]}{s_p s[F(H)]}. \quad (4)$$

Otherwise, only individuals in $N_1, \dots, N_{\bar{G}-1}$ eventually consume the new product, where $\bar{G}$ follows:

$$\bar{G} = \min k \text{ where } \frac{v_H - H_{N_k}}{v_L - H_{N_k}} \leq \frac{[s[F(H_{N_k}) - 1] + 1]}{s_p s[N - F(H_{N_k})]}.$$

Proposition 2 presents intuitive comparative statics on the asymptotic market share of the new product. The new product’s asymptotic market increases when individuals discount others’ experiences less, for example when they have similar preferences or strong social ties; when the new product is much more superior; when the learning speed about the new product is much faster than that about the incumbent product; or when individuals have high aspiration levels and thus are more willing to experiment.

As the new product is superior, the asymptotic market share of the new product sheds light not only on the surplus of the new firm, but also on the upper bound of social efficiency. It corresponds to situations where experiences propagate in society quickly, such that the duration between periods is small and future payoffs are not discounted. As time goes to infinite, the more individuals consume the new product, the higher the social welfare is. The following two sections shed light on situations where future payoffs are discounted.

Although asymptotic inefficiency is also present in the existing Bayesian model, the mechanism in the current setup contrasts with theirs, leading to different policy implications. In particular, in the existing literature, asymptotic inefficiency results from the lack of information about the innovation (Frick and Ishii (2024), Board and Meyer-ter Vehn (2021), Banerjee (1992)).³ In contrast, in this paper, individuals incorporate early adopters’ consumption experiences of the innovation and ultimately collect infinite cases showing that the new product yields a higher payoff than the incumbent product. If individuals are Bayesian, this infinite stream of good signals about the innovation will ultimately drive everyone to consume the new product. However, in CBDT, the good experiences of the new products are overwhelmed by the volume of the experiences of the incumbent product, even though they yield a lower payoff. It captures individuals’ tendency to satisfice: a decent product with many reviews is better than a superior product with fewer reviews. Unlike in a Bayesian model, this novel mechanism implies that marketing campaigns that keep sending information about the new product may not succeed in increasing market share and preventing asymptotic inefficiency.

³For example, in herding model, a few bad experiences of the innovation leads to non-adoption: Consumers become pessimistic and are not willing to experiment. Thus, no additional information about the new product is collected and shared.

5 Product Specifications and Marketing Strategies: Initial Speed v.s. Acceleration

Given the characterization of the adoption process, I now analyze the role of the characteristics of the new product. More specifically, I compare the diffusion process of two specifications of the new product, (v_H, s_p) and (v'_H, s'_p) , fixing other model parameters. As discussed in the model setup, v_H and s_p capture different aspects of product designs or marketing campaigns. For example, a higher v_H could capture higher quality or a higher spending on R&D, while a higher s_p could capture less customization, innovations primarily based on the incumbent product, or more investment in marketing campaigns. According to Proposition 1, the two product specifications induce two adoption processes characterized by two sequences of thresholds. Denote the two sequences of thresholds by $\underline{H}_1, \underline{H}_2, \dots$ and $\underline{H}'_1, \underline{H}'_2, \dots$ respectively.

The following Lemma shows that increasing v_H (resp. s_p) while keeping fixed s_p (resp. v_H) decreases $\underline{H}_t$ for all $t \geq 2$, i.e., the product with higher v_H and/or s_p diffuses faster in the market.

Lemma 2. *Consider two products where one has a higher quality and learning speed. In all periods, the product with a higher quality and learning speed diffuses faster and covers a larger market. Formally, consider (v_H, s_p) and (v'_H, s'_p) where $(v'_H, s'_p) \geq (v_H, s_p)$. For all t , $\underline{H}_t \geq \underline{H}'_t$.*

Lemma 2 shows that a product specification (v'_H, s'_p) dominates another product specification (v_H, s_p) if $(v'_H, s'_p) \geq (v_H, s_p)$, i.e., the former covers a larger market than the latter in each period $t \geq 2$. The following Proposition looks into the more interesting case where no product specification dominates the other, i.e., $(v'_H - v_H)(s'_p - s_p) < 0$.

Proposition 3. *Consider two product specifications (v'_H, s'_p) and (v_H, s_p) where neither covers a larger market in all periods than the other. The product with higher quality covers a larger market in earlier periods, but a smaller market in later periods.*

Formally, suppose without loss of generality that $\underline{H}_2 < \underline{H}'_2$, i.e., (v_H, s_p) sells more than (v'_H, s'_p) in period 2.^{4,5} When at least one of $\underline{H}_t, \underline{H}'_t$ is not $-\infty$, we have:

⁴The condition holds when $s_p \frac{v_H - \underline{H}'_2}{v_L - \underline{H}_2} > s'_p \frac{v'_H - \underline{H}'_2}{v_L - \underline{H}'_2} = \frac{s(2N - N_1 - 2) + 2}{sN_1}$, for example when v_H is big enough compared to v'_H or when s_p is big enough compared to s'_p .

⁵Note that when $\underline{H}_2 = \underline{H}'_2$, the second bullet point of the Proposition continues to hold. On the other hand, for the first bullet point, we have if $s_p > s'_p$, $\underline{H}_t \leq \underline{H}'_t$ for all $t \geq 3$. Moreover, if $s_p > s'_p$ and $N_1 \subset D_n^{t'}$ for some t' , there exists $\underline{t} > t'$ such that $\underline{H}_t < \underline{H}'_t$ for all $t \geq \underline{t}$.

1. if $s_p > s'_p$, $\underline{H}_t < \underline{H}'_t$ for all $t \geq 3$;
2. if $s_p < s'_p$, either
 - (a) $\underline{H}_t \leq \underline{H}'_t$ for all $t \geq 3$, or;
 - (b) there exists a $\tilde{t} \geq 2$ such that $\underline{H}_t \leq \underline{H}'_t$ if and only if $t \leq \tilde{t}$.

The Proposition shows an interesting difference between the diffusion patterns of a non-dominated pair of product specifications. Figure 1 illustrates the result. Borrowing terminologies in Bass (1969), the diffusion patterns of the two product specifications differ in their initial speed and acceleration. The result suggests that radical innovation, i.e., a product with high v_H but low s_p , diffuses quicker among consumers who are more willing to experiment but could fail to maintain momentum in the later stage of diffusion. On the other hand, incremental innovation, i.e., a product with low v_H but high s_p , diffuses more slowly at the beginning but is better at maintaining/gaining momentum.⁶ Thus, given two innovations with the same asymptotic level of adoption, an impatient social planner/firm would prefer a more radical innovation that delivers a higher initial speed of adoption. In contrast, a patient social planner/firm would prefer a more incremental innovation.

Similarly, with the interpretation that s_p captures marketing expenditure and v_H captures R&D expenditure, the Proposition suggests that a new product with higher R&D expenditure would sell better in the initial stages, while a new product with higher marketing expenditure will enjoy a larger market share as time goes on. This resonates with a quote by Dave Dickinson, the former CEO of Zeo, Inc., a company that developed innovative sleep-monitoring devices: *“Early on, we realized that our ability to transcend our customer base, from highly-engaged, “quantified self” early adopters to the mainstream world of the “frustrated sleepers”, would require far more than just the raw data itself. It turns out that the gift wrapping matters as much as the present inside.”*⁷ The quote emphasizes the importance of investment in marketing campaigns for innovation to penetrate the market, selling to the broader crowd beyond the early enthusiasts.

⁶The following example illustrates why radical (resp. incremental) innovation corresponds to a high (resp. low) v_H but low (resp. high) s_p . Consider a product that is composed of multiple features. Replacing each feature with a new technology increases consumption payoff but decreases learning rate, as the product becomes more complicated and less similar to existing technology. Radical innovation corresponds to a product design where many features are replaced, thus giving a high payoff but a low similarity with the original product. The opposite holds for incremental innovation.

⁷See <https://www.mobihealthnews.com/22410/can-personal-health-data-motivate-behavioral-change-it-depends/>.

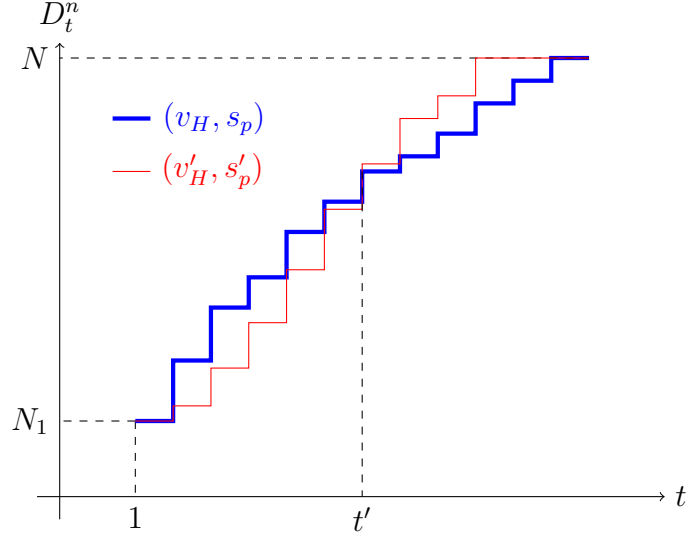


Figure 1: An example of diffusion patterns of two non-dominated product specifications (v_H, s_p) and (v'_H, s'_p) where $v_H > v'_H$ but $s_p < s'_p$. Product (v_H, s_p) diffuses faster at the beginning but slower as t grows larger.

The intuition of the Proposition is as follows. As shown in Proposition 1, at the beginning of the diffusion process, individuals with high aspiration levels, i.e., innovators or early majorities a la Rogers (2010), adopt the new product. Those individuals value high quality more than individuals with low aspiration levels: the marginal increase in $\frac{v_H - H}{v_L - H}$ w.r.t. v_H increases in H . As a result, products with higher quality attract early adopters better than products with higher similarity and thus cover a larger market at the beginning of the diffusion process. In contrast, at the later stage of the diffusion process, the adoption decisions of individuals with lower aspiration levels matter. Those individuals value high quality less and will only adopt the new product when there is sufficient knowledge of the new product in the market: their decision depends more on the volume of good experiences than the quality of the product. Thus, as an incremental innovation enjoys a larger knowledge spillover from the incumbent product and a faster learning rate, it sells better to individuals with lower aspiration levels, thus covering a larger market in the later stage of diffusion.

This novel trade-off between initial speed and acceleration contrasts with the existing literature and offers important economic implications. First, in the existing literature on network contagion models, for example, the word-of-mouth model (Campbell (2013)), or models where individuals adopt if a sufficient proportion of their neighbors adopt (Jackson and Yariv (2006)), there is no trade-off between initial speed and acceleration of diffusion. If product A sells to more individuals at

the beginning than product B, those initial sales help the product diffusion. Thus, product A will also enjoy a higher acceleration of diffusion than product B. The argument also applies to Bayesian models. Assuming no price difference between the two superior new products, if a product diffuses faster at the beginning, it generates more favorable information and thus enjoys a higher acceleration of diffusion. Moreover, these contagion models predict that diffusion is slow at the beginning and picks up the pace once a substantial amount of people have adopted a new product. In contrast, Proposition 3 shows that products with higher v_H and low s_p diffuse faster at the beginning and slow down eventually, which is documented by a recent empirical study (Jin et al. (2019)).

Second, the mechanism driving Proposition 3 highlights a natural difference between the preferences of early and late adopters. Early adopters are often enthusiasts of the product/technology, more willing to experiment, and are more sensitive to technological advancement and quality. Late adopters, however, are satisficers and will adopt a new product only if they collect lots of favorable evidence. Such a difference is not present in network contagion models, despite being recognized by business executives, e.g., the former CEO of Zeo Inc. distinguishes the “quantified self” early adopters from the mainstream “frustrated sleepers” and emphasizes the importance of marketing when selling to the latter group of consumers. Furthermore, there are many examples of innovation that industry leaders and tech enthusiasts hype but ultimately fail and exit the market. For example, Segway PT was endorsed by Steve Jobs and Jeff Bezos as “significant as the personal computer” and “revolutionary” but failed to become mainstream, and only 140,000 units were sold during the lifetime of the product.⁸

Third, Proposition 3 provides micro-foundation of the two important parameters, i.e., initial speed and acceleration of macro-diffusion models, for example, the Bass model (Bass (1969)) and epidemic models (e.g., Pastor-Satorras et al. (2015)). It suggests that different types of innovations appeal to consumers with different tendencies to satisfice, and thus sell better in different stages of the diffusion dynamics.

5.1 Inferior Innovation

Before presenting the results on social networks in the next Section, I discuss how inferior innovation changes the characterization of the diffusion process.

The assumption that the new product is superior to the incumbent product, i.e.,

⁸See <https://slate.com/human-interest/2021/08/dean-kamen-viral-mystery-invention-2001.html>.

$v_H > v_L$, is crucial for Lemma 1. In contrast, if $v_H < v_L$, i.e., the new product is inferior, then individuals will switch back to the incumbent product after adopting the new product. The larger $v_L - v_H$ is, the more likely individuals will return to the incumbent product. Such a switchback rate is thus an empirical indicator of the quality of the innovation. For example, after its launch in 2011, the social media platform Google+ saw a “98% year-over-year” decrease in engagement rate and was eventually shut down in 2019.⁹

6 Social Network and Diffusion

In this section, I analyze and discuss the effect of social networks, i.e., $(s_{i,j})$, on product diffusion. In recent years, with technological advances and social media, it has become increasingly easier for consumers to share and search for reviews of new products. It leads to stronger network ties between consumers. On the other hand, there are concerns that recommendation algorithms and social media create echo chambers and increase homophily.¹⁰ In the following, I show in two simple settings how homophily and stronger network ties, driven by technological advances in recent years, affect diffusion.

First, moving away from the assumption that $s_{i,i} = 1$ and $s_{i,j} = s$ for all $i \neq j$, Lemma 1 continues to hold. That is, individuals never consume the incumbent product after adopting the new product. However, Proposition 1 may not hold. In particular, an individual with a lower aspiration level will adopt the new product earlier if he is better connected to individuals who adopt the new product in earlier periods (for example, individuals in N_1).

6.1 Homophily

I first analyze how homophily, i.e., the tendency of individuals to form closer links with others who are similar to themselves, affects product diffusion. For simplicity, I model homophily with the following assumption on $s_{i,j}$:

$$s_{i,j} = \begin{cases} 1 & \text{when } i = j; \\ \gamma s & \text{when } i \neq j \text{ and } i, j \in N_k \text{ for some } k; \\ s & \text{otherwise.} \end{cases}$$

⁹See <https://www.forbes.com/sites/stevedenning/2015/04/23/has-google-really-died/?sh=2d2c9f65466c> and <https://www.theverge.com/2019/4/2/18290637/google-plus-shutdown-consumer-personal-account-delete>.

¹⁰See, for example, Berman and Katona (2020) and Ross Arguedas et al. (2022).

where $\gamma \in (1, \frac{1}{s})$. An increase in γ captures an increase in homophily. Furthermore, for simplicity, I assume that all groups of individuals are of the same size, i.e., $N_i = N_j = \frac{N}{G}$ for all $i, j = 1, \dots, G$.¹¹

Proposition 4. *An increase in homophily slows down the diffusion process. Formally, the diffusion process is characterized by a sequence of decreasing thresholds $\underline{H}_t \in \mathbb{R} \cup \{-\infty\}$ such that all and only individuals whose aspiration level $H_i > \underline{H}_t$ consume the new product in period t . An increase in γ increases $\underline{H}_t$ for all $t \geq 2$.*

The intuition is as follows. First, note that individuals in the same group always adopt the new product at the same time. When an individual in the group N_k has not yet adopted the new product, it implies that other individuals in the same group have only consumed the incumbent product in all previous periods. As a result, an increase in homophily implies that individuals take into account more experiences of the incumbent product before they adopt the new product, which slows down the diffusion process of the innovation. A key insight here is that innovation adoption relies a lot on the spillover of social learning: individuals adopt the innovation only after seeing enough good experiences from others in society. As individuals with similar characteristics tend to make similar decisions, they adopt the innovation only based on the experiences of individuals who are different from them, specifically those who are more adventurous and willing to experiment. A higher level of homophily reduces this inter-group interaction and thus slows innovation adoption.

This result, combined with Proposition 2, suggests word-of-mouth communication is a double-edged sword for innovation diffusion. On the one hand, Proposition 2 shows that word-of-mouth induces a spillover of information/experience from the early adopters to the rest of the market, prompting individuals with lower aspiration levels to switch to the more superior new product. On the other hand, as consumers tend to value word-of-mouth from strong ties (Brown and Reingen (1987)), e.g., families and close friends, it could reinforce the word-of-mouth for the incumbent product and limit the adoption of innovation. For example, because of their stigma towards vegans, people with omnivorous diets might be uninformed about the potential health benefits of a plant-based diet, which limits its adoption (Markowski and Roxburgh (2019); Rickerby and Green (2024)).

¹¹When different groups of individuals have different size, under this setting of homophily, there is also a group size effect as homophily has a bigger effect on consumers from a larger group: individuals from a larger group will have less incentive to adopt the new product. As a result, individuals with higher aspiration levels and also a larger group size may not adopt the new product in earlier periods. Assuming that all groups have the same size allows me to highlight the effect of homophily better.

6.2 Network ties based on Aspiration Level

Next, I look into the case where for each $k = 1, \dots, G$, $s_{i,j}$ are invariant across all $i \neq j \in N_k$, and $s_{i,i} = 1$ for all i . That is, the strength of the connection between i and j only depends on which group j belongs to. This allows me to analyze how the increased or decreased influence of each group affects diffusion. For the ease of exposition, s_{N_k} denotes $s_{i,j}$ where $j \in N_k$ for all i , and I call $(s_{N_k})_{k=1}^G$ a social network. Note that, different from previous sections, the diffusion process here is not characterized by a decreasing sequence of thresholds on aspiration level.¹² Nonetheless, individuals do not consume the incumbent product once they switch to the new product; the model remains tractable, and we have the following results.

Proposition 5. *Innovation diffuses faster if network ties among individuals uniformly increase, or network ties towards individuals with higher aspiration levels increase in a large society. Formally, consider two social network $(s_{N_k})_{k=1}^G$ and $(s'_{N_k})_{k=1}^G$ and their demand at each period (D_c^t, D_n^t) and $(D_c'^t, D_n'^t)$. Innovation diffuses faster with $(s'_{N_k})_{k=1}^G$ than with $(s_{N_k})_{k=1}^G$, i.e., $D_n^t \subseteq D_n'^t$, i.e., if*

1. $(s'_{N_k})_{k=1}^G = z(s_{N_k})_{k=1}^G$ where $z \in [1, \frac{1}{\max_k s_{N_k}}]$, or
2. N is large enough,¹³ and $\exists k > k'$ such that

$$N_k(s'_{N_k} - s_{N_k}) = N_{k'}(s_{N_{k'}} - s'_{N_{k'}}) > 0.$$

and $s_{N_{k''}} = s'_{N_{k''}}$ for all $k'' \neq k, k'$.

Proposition 5 shows two sufficient conditions where the innovation diffuses faster in social network $(s_{N_k})_{k=1}^G$ than in social network $(s'_{N_k})_{k=1}^G$.

The first condition shows that when the network ties are stronger, the diffusion of the new product improves. Note that the network ties with individuals with both higher and lower aspiration levels are strengthened. The result thus shows that the innovation diffusion is improved as long as the network ties with early adopters are strengthened to a similar degree as the network ties with late adopters. It is contrary

¹²For example, consider a setting with three individuals and three groups N_1, N_2, N_3 , where $H_{N_2} \approx H_{N_3}$. Suppose $s_{N_1}, s_{N_3} \approx 1$ and $s_{N_2} \approx 0$, and the individual in N_1 consumes the new product. Thus, the individual in N_2 put weight s_{N_1} close to 1 on the experience of the new product and weight close to 2 (because that $s_{i,i} = 1$ for all i) on the experience of the incumbent product; while the individual in N_3 put weight s_{N_1} close to 1 on the experience of the new product, and weight close to 1 on the experience of the incumbent product. As a result, individuals in N_3 adopt the innovation earlier than individuals in N_2 .

¹³The condition that N is big enough ensures that the diffusion is characterized by a decreasing sequence of thresholds on aspiration level, so that “early adopters” are well defined by their high aspiration levels.



Figure 2: Amazon ranks reviewer and gives badges to top reviewers which makes their reviews more prominent.

to contagion models, where individuals adopt the new product only if more than a fixed proportion of their neighbors have adopted it, as strengthening ties with both early and late adopters does not help diffusion. Also note that this result holds only because the new product is superior to the incumbent product, i.e., $v_H > v_L$. It thus suggests that a better-connected network will help differentiate good and bad products by boosting the former's diffusion and stalling the latter's diffusion.

The second condition shows that, unsurprisingly, when society is more exposed to reviews/experiences of innovators, who have less tendency to satisfice and are more inclined to experiment, other individuals would accumulate knowledge about the new product faster and switch to new products earlier. The increased exposure of innovators could be driven by increased attention based on people's perception that innovators can evaluate new products better. It could also be driven by platform strategies highlighting reviews written by consumers who leave more (and more helpful) reviews. The result suggests that platform strategies that highlight reviews of individuals who frequently purchase new products would help innovation diffusion and increase the incentive of firms to innovate, ultimately improving the product offerings and value of the platform. For example, Figure 2 shows that Amazon highlights reviews from top reviewers who frequently test new products and share reviews. Similarly, the Amazon Vine program invites insightful reviewers to try and review products for free and distinguishes their reviews with a special badge "Vine Customer Review of Free Product".¹⁴

7 Managerial Implications

I now discuss the policy and managerial implications of the results. They apply to firms that aim to design, produce and sell new products, platforms that aim to promote innovation and new product adoption, as well as governments or NGOs that aim to promote technologies that advance societal health and economic growth.

¹⁴See <https://www.amazon.com/vine/about>.

The limitation of word-of-mouth marketing. Amazon founder Jeff Bezos once said: *“If you build a great experience, customers tell each other.”*, lauding the effectiveness of word-of-mouth marketing.¹⁵ In another interview, he also said that the internet has made word-of-mouth more powerful, and thus it is more important to build a good product than to market it.¹⁶

This paper, however, shows a more nuanced role of word-of-mouth marketing in that it is a double-edged sword. On the one hand, word-of-mouth marketing allows experiences to spill over and propagate in the market: more adventurous consumers who have tried a new product share their good experiences with less adventurous consumers, allowing the latter group to collect information and adopt the goods themselves. However, the same tactic works for a good enough incumbent product. More specifically, incumbent firms can use word-of-mouth marketing to overwhelm those with a new superior product. This is particularly true when consumers are satisficers and therefore cautious, with a high level of homophily and the presence of echo chambers, or when the incumbent product has a large and loyal consumer base. In these circumstances, it is unlikely that word-of-mouth from a small set of early adopters would affect the purchasing behavior of the general public. For example, despite receiving good reviews from early adopters and being ranked the 2nd most sold MP3 units during its launch week, Microsoft Zune failed to challenge the market leader, the Apple iPod. Part of the reason is that the Apple iPod was launched 5 years ago and has already cemented its leading position.¹⁷ Similarly, despite being hailed by tech moguls like Steve Jobs and Jeff Bezos, Segway PT remained a niche product and was eventually discontinued in 2020, failing to change the commuting habits of society.

The difference between seeding/word-of-mouth marketing and consumer education. There are, of course, many different marketing strategies beyond the word-of-mouth marketing. This model allows us to discuss the differences between seeding/word-of-mouth marketing and consumer education. Seeding/word-of-mouth marketing refers to the spillover of experiences from one consumer to another, while consumer education could be captured by the parameter s_p and how quickly consumers learn about the new product.

¹⁵See <https://www.bloomberg.com/news/articles/2004-08-01/online-extra-jeff-bezos-on-word-of-mouth-power>.

¹⁶See <https://www.forbes.com/forbes/2012/0423/ceo-compensation-12-amazon-technology-jeff-bezos-gets-it.html>.

¹⁷See <https://www.engadget.com/2006-11-29-zune-takes-2-spot-in-retail-launch-week.html> for the sales figure, and <https://www.silicon.co.uk/mobility/smartphones/tales-tech-history-microsoft-zune-210569> on the comparison between Zune and iPod.

As previously mentioned, word-of-mouth marketing is limited in facilitating the adoption of new products. Word-of-mouth marketing is more powerful for incumbent products with a large following and a loyal consumer base than for a new product with a small consumer base. In contrast, consumer education affects consumers and the market landscape differently. More specifically, consumer education asymmetrically increases the learning rate of new and more innovative products. The mere nature of education implies that it teaches and allows consumers to appreciate the new technology’s benefits better, thus favoring the new product against the incumbent product. For example, plant-based meat producers, e.g., Impossible Foods and Beyond Meat, launched multiple educational campaigns to educate consumers on the ingredients and science behind their products and the environmental benefits they bring, which improved their sales massively throughout the years. Examples include a Beyond Meat-commissioned study done by the Center for Sustainable Systems at the University of Michigan to compare the environmental impact of a plant-based and an animal-based protein source,¹⁸ an entire “learn” section on the official website of Beyond Meat dedicated to the benefit, science, and ingredient of its products,¹⁹ and a podcast and cooperation between the American science communicator Bill Nye and Impossible Foods on the benefit and science of plant-based meats.²⁰

Small but familiar innovation diffuses better in the long run. Proposition 3 shows that incremental innovations’ diffusion accelerates better than radical innovations’, although the initial diffusion speed is lower. It emphasizes that a higher quality product may not enjoy a faster diffusion. This is especially true when there are many individuals with low aspiration levels. When satisficing is the main friction of innovation diffusion, i.e., there are many individuals with high tendencies to satisfice, a smaller but easily understandable innovation diffuses better.

The result is supported by Min et al. (2006), which analyzes 264 new industrial product markets. They show that survival is a major challenge when a market pioneer starts a new market with a radically new product. Among the 66 radically new product markets, only 23% of the market pioneers survived for at least 12 years. In contrast, among the 198 incrementally new product markets, 61% of the market pioneers survived for at least 12 years.

As the co-founder of Netscape, Marc Andreessen, said in an interview: “We

¹⁸See <https://css.umich.edu/publications/research-publications/beyond-meats-beyond-burger-life-cycle-assessment-detailed>

¹⁹See <https://www.beyondmeat.com/en-GB/>.

²⁰See <https://www.globalplayer.com/podcasts/episodes/7DrcdWk/>.

almost never see a qualified founder fail because they were too late to market. It’s almost always because they’re too early to market.”²¹ which suggests an advantage of innovations that are “not too new”. In fact, Apple is lauded for its “Second Mover” strategy. Despite not being the first to release a smartphone and smartwatch, Apple dominates both markets across the globe.²² Similarly, Samsung introduced Galaxy AI in January 2024, while Apple announced its Apple Intelligence system only in June 2024, with a full launch scheduled in 2025.

The trade-off between R&D versus Marketing effort. Proposition 3 also highlights the importance of Marketing effort when it comes to the long-term success of the products, while too much focus on R&D may lead to a niche consumer base.

The Proposition is thus in contrast to the idea of “just make a better product and let its quality speak for itself” and the hyper-focus on R&D. In fact, there are many examples of superior new products that eventually failed because of consumers’ reluctance to change and the inefficient or lack of marketing effort. Take the “new Coke” as an example.²³ In 1985, facing stiff competition, the Coca-Cola company decided to change its Coca-Cola formula to a new formula that was preferred in taste tests of nearly 200,000 consumers. However, the supposed superiority of the new formula did not translate to better sales; it only led to outcry and the eventual return of the original Coca-Cola formula in just 79 days. Similarly, in 2012, Google Glass was named one of the “Best Inventions of the Year” by Time Magazine, but it was pulled from the market in 2015.²⁴ Former Microsoft executive Robbie Bach also discussed the inadequate and inefficient marketing effort that led to the failure of Microsoft Zune: *“On the Zune side, ..., I think our marketing message was very confused.”* and *“We did some really artsy ads that appealed to a very small segment of the music space, and we didn’t captivate the broad segment of music listeners.”*²⁵ As mentioned before, Dave Dickinson, the former CEO of Zeo, Inc., also emphasized the importance of marketing when a new product diffuses from the enthusiasts to the rest of the market.

²¹See https://x.com/StartupArchive_/status/1801220481716277580.

²²See <https://www.asmallstudio.com/article/move-fast-and-break-things> and <https://www.businessinsider.com/apple-second-mover-advantage-2015-6>.

²³For reference, see <https://www.coca-colacompany.com/about-us/history/new-coke-the-most-memorable-marketing-blunder-ever>.

²⁴See <https://techland.time.com/2012/11/01/best-inventions-of-the-year-2012/slide/google-glass/> and <https://www.nytimes.com/2015/02/05/style/why-google-glass-broke.html>.

²⁵See <https://www.geekwire.com/2012/robbie-bachs-lessons-intrapreneurship-xbox-zune/> <https://www.businessinsider.com/robbie-bach-explains-why-the-zune-flopped-2012-5>.

The design of platform and network ties on innovation diffusion. Last but not least, our result provides important insights for platforms and social planners on incentivizing the adoption of new and superior products. As a result, it would incentivize efforts to innovate and increase the value of the platform and the society’s utility.

First, uniformly strengthening social ties or promoting a culture of sharing experiences helps in innovation diffusion. It allows experiences of innovations to propagate across the platform or society. For example, iOS and Android API allow app developers to show in-app rating prompts that encourage users to leave reviews and ratings.²⁶ It is reported that Instagram has doubled the number of its iOS ratings in a week thanks to the in-app rating prompts.²⁷ Similarly, Google also provides tips and guidelines for businesses to encourage consumers to post reviews, for example by reminder, verification and responding to consumers’ review to improve engagement.²⁸

Second, platforms can asymmetrically increase the prominence of reviews from early versus late adopters. As shown in Proposition 5, such a policy increases the exposure of new products and allows consumers to benefit from others’ experimentation. In terms of implementation, platforms can increase the prominence of reviewers who actively try new products by recruiting them into programs like Amazon Vine, sorting reviews based on the helpfulness of reviews, or increasing the weights of helpful reviews when aggregating or summarizing consumers’ reviews. For example, both Trustpilot and Google sort the reviews based on multiple factors, including their helpfulness, length, authenticity, etc.²⁹ Moreover, Amazon does not report the simple average of consumers’ ratings but calculates an aggregated star rating based on “machine-learned models” and uses “AI” to summarize multiple consumers’ reviews as the “Customers Say Review Highlights”.³⁰ All these features allow platforms to disproportionally increase the weight and prominence of reviews from early adopters.

²⁶See, for example, <https://stories.appbot.co/my-ios-ratings-prompt-verdict-4bcc0a834358>.

²⁷See <https://medium.com/huggingface/instagram-doubled-its-ios-reviews-in-a-week-thanks-to-this-new-in-app-review-popup-52333d4f4ce6>.

²⁸See https://support.google.com/business/answer/3474122?hl=en&ref_topic=4596755&sjid=17305854190903168593-EU.

²⁹See <https://support.trustpilot.com/hc/en-us/articles/10832763560722-How-reviews-are-sorted-on-Trustpilot> and <https://www.mara-solutions.com/post/google-most-relevant-reviews-criteria>.

³⁰See https://www.amazon.co.uk/gp/help/customer/display.html?ref_=hp_left_v4_sib&nodeId=G8UYX7LALQC8V9KA.

8 Conclusion

This paper examines how consumer, product, and social network characteristics influence the diffusion of a superior innovation among case-based individuals. A key element of the model is that individuals have heterogeneous tendencies to satisfice. As a result, the adoption of the superior innovation might come to a standstill as the information about the incumbent product overwhelms the information about the superior innovation.

Furthermore, individuals with lower tendencies to satisfice tend to adopt the superior innovation earlier compared to those with stronger tendencies to satisfice. That is why radical innovations and innovations with a strong R&D focus diffuse at a higher initial speed but with lower acceleration, compared to incremental innovations and innovations with a strong marketing focus. Lastly, innovations diffuse faster in a closely knitted society, or when ties towards early adopters are strengthened. These results provide important managerial and marketing implications regarding the trade-off between R&D and marketing, as well as how platforms and governments can encourage innovation and its adoption.

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A Proofs

A.1 Proof of Lemma 1

Proof. I prove by induction that individuals who choose the new product in period t will choose the new product in period $t + 1$ for all t , i.e., $D_n^t \subseteq D_n^{t+1}$ for all t . The Lemma then follows.

First note that in period 1, only individuals in N_1 choose the new product: $U_i^1(p_c) = s_{p_c, p_c}((N - 1)s + 1)(v_L - H_i)$ is strictly smaller than $U_i^1(p_n) = s_{p_n, p_c} U_i^1(p_c)$ if and only if $H_i > v_L$, as $s_{p_c, p_c} > s_{p_n, p_c}$. In period $t \geq 2$, for $i \in N_1$,

$$\begin{aligned}
& U_i^t(p_n) - U_i^t(p_c) \\
&= s_{p_n, p_c} \sum_{t'=0}^{t-1} \sum_{j \in D_c^{t'}} s_{i,j}(v_L - H_{N_1}) + s_{p_n, p_n} \sum_{t'=0}^{t-1} \sum_{j \in D_n^{t'}} s_{i,j}(v_H - H_{N_1}) \\
&\quad - s_{p_c, p_c} \sum_{t'=0}^{t-1} \sum_{j \in D_c^{t'}} s_{i,j}(v_L - H_{N_1}) - s_{p_c, p_n} \sum_{t'=0}^{t-1} \sum_{j \in D_n^{t'}} s_{i,j}(v_H - H_{N_1}) \\
&= -[s_{p_c, p_c} - s_{p_n, p_c}] \sum_{t'=0}^{t-1} \sum_{j \in D_c^{t'}} s_{i,j}(v_L - H_{N_1}) + [s_{p_n, p_n} - s_{p_c, p_c}] \sum_{t'=0}^{t-1} \sum_{j \in D_n^{t'}} s_{i,j}(v_H - H_{N_1}) \\
&> 0
\end{aligned}$$

where the inequality is implied by $s_{p_c, p_c} - s_{p_n, p_c} > 0$, $s_{p_n, p_n} - s_{p_c, p_c} > 0$ and $v_H \geq H_{N_1} > v_L$. Thus, individuals in N_1 choose new product in all period $t \geq 1$. $D_n^1 \subseteq D_n^t$ for all $t \geq 1$.

Now suppose $D_n^{t-1} \subseteq D_n^t$ for all $t = 2, \dots, T$, I proceed to prove $D_n^T \subseteq D_n^{T+1}$. First note that $U_i^t(p_n) > U_i^t(p_c)$ if and only if

$$\begin{aligned}
& (s_{p_n, p_n} - s_{p_c, p_n}) \sum_{t'=0}^{t-1} \sum_{j \in D_n^{t'}} s_{i,j}(v_H - H_i) > (s_{p_c, p_c} - s_{p_n, p_c}) \sum_{t'=0}^{t-1} \sum_{j \in D_c^{t'}} s_{i,j}(v_L - H_i); \\
& s_p \sum_{t'=0}^{t-1} \sum_{j \in D_n^{t'}} s_{i,j}(v_H - H_i) > \sum_{t'=0}^{t-1} \sum_{j \in D_c^{t'}} s_{i,j}(v_L - H_i); \\
& s_p \sum_{t'=0}^{t-1} \Delta_{t', n}(H_i) > \sum_{t'=0}^{t-1} \Delta_{t', c}(H_i)
\end{aligned} \tag{5}$$

where $\Delta_{t,n}(H_i) \equiv \sum_{j \in D_n^t} s_{i,j}(v_H - H_i)$ and $\Delta_{t,c}(H_i) \equiv \sum_{j \in D_c^t} s_{i,j}(v_L - H_i)$. Next, as $D_n^T = (D_n^T \setminus D_n^{T-1}) \cup (D_n^{T-1} \setminus D_n^{T-2}) \cup \dots \cup (D_n^2 \setminus D_n^1) \cup D_n^1$, it suffices to prove $D_n^t \setminus D_n^{t-1} \subseteq D_n^{t+1}$ for $t = 2, \dots, T$. I have already proved above that $D_n^1 \subseteq D_n^{T+1}$.

For individuals in $D_n^2 \setminus D_n^1$, as they choose the incumbent product in period 1 but the new product in period 2, it must be that the increase of the left-hand side of Inequality (5) (from period 1 to period 2) is strictly greater than the increase of the right-hand side of the Inequality, i.e., $\Delta_{1,n}(H_i) > \Delta_{1,c}(H_i)$ for $i \in D_n^2 \setminus D_n^1$. Next, as $D_n^1 \subseteq D_n^{t'}$ and $D_c^{t'} \subseteq D_c^1$ for all $t' = 2, \dots, T$ (by inductive assumption), for $i \in D_n^2 \setminus D_n^1$ and all $t' = 2, \dots, T$,

$$\begin{aligned} s_p \Delta_{t',n}(H_i) &= s_p \sum_{j \in D_n^{t'}} s_{i,j}(v_H - H_i) \geq s_p \sum_{j \in D_n^1} s_{i,j}(v_H - v_L) \\ &> \sum_{j \in D_c^1} s_{i,j}(v_L - H_i) \geq \sum_{j \in D_c^{t'}} s_{i,j}(v_L - H_i) = \Delta_{t',c}(H_i). \end{aligned}$$

Combining with the fact that $s_p \sum_{t'=0}^1 \Delta_{t',n}(H_i) > \sum_{t'=0}^1 \Delta_{t',c}(H_i)$ for $i \in D_n^2 \setminus D_n^1$, we have $s_p \sum_{t'=0}^T \Delta_{t',n}(H_i) > \sum_{t'=0}^T \Delta_{t',c}(H_i)$ and therefore $D_n^2 \setminus D_n^1 \subseteq D_n^{T+1}$. Continuing the same procedure implies that individuals in $D_n^t \setminus D_n^{t-1}$ for $t = 3, \dots, T$ choose the new product in period $T + 1$. The result follows. $\square$

A.2 Proof of Proposition 1

Proof. I prove the first part of the Proposition by induction. As shown in the proof of Lemma 1, in period 1, only individuals with aspiration level $H_i > v_L$ consume the new product in period 1, i.e., $\underline{H}_1 = v_L$.

Now suppose in period $t = 2, \dots, T$, there exists a unique threshold $\underline{H}_t$ such that all and only individuals whose aspiration level $H_i > \underline{H}_t$ consume the new product. Now given Lemma 1, in period $T + 1$, individuals with aspiration level strictly greater than $\underline{H}_T$ will continue to consume the new product. For an individual i with $H_i \leq \underline{H}_T$, he chooses the new product in period $T + 1$ if and only if Inequality (5) holds:

$$s_p \sum_{t'=0}^T \sum_{j \in D_n^{t'}} s_{i,j}(v_H - H_i) > \sum_{t'=0}^T \left[s(D_c^{t'} - 1) + 1 \right] (v_L - H_i).$$

If $s_p \sum_{t'=0}^T \sum_{j \in D_n^{t'}} s_{i,j} \geq \sum_{t'=0}^T \left[s(D_c^{t'} - 1) + 1 \right]$, all individuals consume p_n as $v_H > v_L$, thus we set $\underline{H}_{T+1} = -\infty$ and the result follows. If $s_p \sum_{t'=0}^T \sum_{j \in D_n^{t'}} s_{i,j} < \sum_{t'=0}^T \left[s(D_c^{t'} - 1) + 1 \right]$, the inequality then holds if and only if H_i is big enough. Combing the two cases, there exists a unique threshold $\underline{H}_{T+1}$ such that only and all individuals whose aspiration level $H_i > \underline{H}_{T+1}$ consume the new product in period $T + 1$. The first part of the Proposition thus follows. The second part of the Proposition is immediately implied by Lemma 1. $\square$

A.3 Proof of Proposition 2

Proof. I first prove the “if” statement of the first part of the Proposition. Suppose that there does not exist a $H_i \in [H_{N_G}, H_{N_1})$ such that

$$\frac{v_H - H_i}{v_L - H_i} \leq \frac{[s[N - F(H_i) - 1] + 1]}{s_p s[F(H_i)]}.$$

It implies that for all $H_i \in [H_{N_G}, H_{N_1})$,

$$\begin{aligned} \frac{v_H - H_i}{v_L - H_i} &> \frac{[s[N - F(H_i) - 1] + 1]}{s_p s[F(H_i)]} \\ s_p s[F(H_i)](v_H - H_i) &> [s(N - F(H_i) - 1) + 1](v_L - H_i) \\ s_p \sum_{j: H_j > H_i} s(v_H - H_i) &> \sum_{j: H_j \leq H_i} s_{i,j}(v_L - H_i). \end{aligned}$$

That is, consider at period t an individual with aspiration level H_i who have yet consumed the new product, and suppose all other individuals with aspiration levels higher than H_i consume the new product at period t . Then, given the consumption cases in period t , we have $s_p \Delta_{t,n}(H_i) > \Delta_{t,c}(H_i)$. The same holds for all period $t' > t$. Thus, individual i adopts the new product in some finite time $T = t + \lceil \frac{U_i^t(p_c) - U_i^t(p_n)}{s_p \Delta_{t,n}(H_i) - \Delta_{t,c}(H_i)} \rceil$. Using induction arguments and the fact that individuals in N_1 adopt the new product in period 1, all individuals adopt p_n in finite time.

Now I prove the “only if” statement. Suppose to the contrary there exists some $H_i \in [H_{N_G}, H_{N_1})$ such that

$$\frac{v_H - H_i}{v_L - H_i} \leq \frac{[s[N - F(H_i) - 1] + 1]}{s_p s[F(H_i)]}.$$

Also without loss suppose that $H_i \in [H_{N_k}, H_{N_{k-1}})$ for some $k \in \{2, \dots, G\}$, it implies that

$$\begin{aligned} \frac{v_H - H_{N_k}}{v_L - H_{N_k}} &\leq \frac{v_H - H_i}{v_L - H_i} \\ &\leq \frac{[s[N - F(H_i) - 1] + 1]}{s_p s[F(H_i)]} = \frac{[s[N - F(H_{N_k}) - 1] + 1]}{s_p s[F(H_{N_k})]}. \end{aligned}$$

It in turn implies that, as $v_L > H_{N_k}$ and $v_H > v_L$,

$$s_p \sum_{j: H_j > H} s(v_H - H_{N_k}) \leq \sum_{j: H_j \leq H} s_{i,j}(v_L - H_{N_k})$$

for all $H \geq H_{N_k}$. Combined with the fact that only consumers in $N_{k'}$ where $k' <$

k would have adopted the new product before consumers in N_k , it implies that $s_p \Delta_{t,n}(H_i) < \Delta_{t,c}(H_i)$ for $i \in N_k$ and for all t . Thus, consumers in N_k never adopt the new product.

For the second part of the Proposition, note that implied by the proof of the first part of the Proposition, individuals in $N_{\bar{G}}$ will not adopt the new product and individuals in $N_1, \dots, N_{\bar{G}-1}$ will adopt the new product in finite time. Lastly, when $F(H_i)$ increases in the sense of F.O.S.D., $\frac{[s(N-F(H_i)-1)+1]}{s_p s[F(H_i)]}$ decreases, the last part of the Proposition follows. $\square$

A.4 Proof of Lemma 2

Proof. In the following, I prove the Lemma in the case where $v'_H > v_H$ and $s'_p = s_p$ by induction. The cases where $v'_H = v_H$ and $s'_p > s_p$, and $v'_H > v_H$ and $s'_p > s_p$ follow similar arguments. At $t = 1$, $\underline{H}_1 = \underline{H}'_1 = v_L$ and $D_n^1 = D_n'^1 = N_1$. At $t = 2$,

$$s_p \sum_{j \in N_1} s(v_H - H_i) < s'_p \sum_{j \in N_1} s(v'_H - H_i),$$

$$[s(2N - N_1 - 2) + 2](v_L - H_i) = [s(2N - N_1 - 2) + 2](v_L - H_i).$$

Thus, individuals who adopt the product (v_H, s_p) will also adopt the product (v'_H, s'_p) , but the reserve is not true, i.e., $\underline{H}_2 > \underline{H}'_2$.

Now suppose $\underline{H}_t > \underline{H}'_t$ for all $t = 3, \dots, T$. It implies that for $t = 1, 2, \dots, T$

$$D_c'^t \subseteq D_c^t \text{ and } D_n^t \subseteq D_n'^t.$$

We thus have

$$\begin{aligned} s_p \sum_{t'=0}^T \sum_{j \in D_n^{t'}} s(v_H - H_i) &\leq s_p \sum_{t'=0}^T \sum_{j \in D_n^{t'}} s(v_H - H_i) \\ &< s'_p \sum_{t'=0}^T \sum_{j \in D_n^{t'}} s(v'_H - H_i) \end{aligned}$$

and

$$\begin{aligned} \sum_{t'=0}^T \left[s(D_c^{t'} - 1) + 1 \right] (v_L - H_i) &\geq \sum_{t'=0}^T \left[s(D_c^{t'} - 1) + 1 \right] (v_L - H_i) \\ &= \sum_{t'=0}^T \left[s(D_c^{t'} - 1) + 1 \right] (v_L - H_i). \end{aligned}$$

The individuals who adopt the product (v_H, s_p) will also adopt the product (v'_H, s'_p) , but the reserve is not true, i.e., $\underline{H}_{T+1} > \underline{H}'_{T+1}$. The result follows. $\square$

A.5 Proof of Proposition 3

Proof. First note that $\underline{H}_{T+1}$ is the solution of

$$s_p \frac{v_H - \underline{H}_{T+1}}{v_L - \underline{H}_{T+1}} = \frac{s \sum_{t=0}^T (D_c^t - 1) + T + 1}{s \sum_{t=0}^T D_n^t}.$$

Define $\lambda_T = \frac{s \sum_{t=0}^T (D_c^t - 1) + T + 1}{s \sum_{t=0}^T D_n^t}$, $\mathcal{F}(H) = s_p \frac{v_H - H}{v_L - H}$ and $\mathcal{F}'(H) = s'_p \frac{v'_H - H}{v'_L - H}$. I first prove that $\mathcal{F}$ and $\mathcal{F}'$ cross at most once for all $H \leq v_L$, which will be useful for the rest of the proof. To see that, note that the first derivative of $\mathcal{F} - \mathcal{F}'$ w.r.t. H equals

$$\frac{\partial(\mathcal{F} - \mathcal{F}')}{\partial H} = \frac{1}{(v_L - H)^2} (s_p(v_H - v_L) - s'_p(v'_H - v'_L))$$

which is monotonic for all $H < v_L$ which implies that $\mathcal{F}$ and $\mathcal{F}'$ cross at most once for all $H \leq v_L$.

I now proceed to prove the first part of the Proposition where $s_p > s'_p$. First note that $\mathcal{F}$ and $\mathcal{F}'$ go to $+\infty$ when $H \nearrow v_L$ and converges to s_p and s'_p respectively as $H \rightarrow -\infty$. Thus, when $s_p > s'_p$, we have either $\mathcal{F}(H) > \mathcal{F}'(H)$ for all H if $s_p(v_H - v_L) \geq s'_p(v'_H - v'_L)$, or otherwise $\mathcal{F}(H) > \mathcal{F}'(H)$ if and only if $H < \tilde{H}$ for some $\tilde{H} \in (-\infty, v_L)$. I first prove the result for the latter case by induction. First, because $\lambda_1 = \lambda'_1$, $\underline{H}_2 < \underline{H}'_2$ implies $\mathcal{F}(H) > \mathcal{F}'(H)$ for all $H \leq \underline{H}'_2$. Next, $\lambda_2 \leq \lambda'_2$, and thus $\underline{H}_3 = -\infty$ if $\underline{H}'_3 = -\infty$. Now suppose $\underline{H}_3, \underline{H}'_3 > -\infty$ and denote $\underline{H}_3(\lambda_2)$ and $\underline{H}'_3(\lambda_2)$ as the solution of $\mathcal{F}(H) = \lambda_2$ and $\mathcal{F}'(H) = \lambda_2$ respectively, we have

$$\underline{H}_3(\lambda_2) \leq \underline{H}_3(\lambda'_2) < \underline{H}'_3(\lambda'_2)$$

where the first inequality is implied by $\lambda_2 \leq \lambda'_2$ and that $\mathcal{F}(H)$ increases in H , while the second inequality is implied by $\mathcal{F}(H) > \mathcal{F}'(H)$ for all $H \leq \underline{H}'_2$ and that $\underline{H}_3, \underline{H}'_3 \leq \underline{H}'_2$.

Now suppose $\underline{H}_t \leq \underline{H}'_t$ for $t = 3, \dots, T$. Note that it implies that $\lambda_t \leq \lambda'_t$ for $t = 3, \dots, T$, and $\underline{H}_{T+1} = -\infty$ if $\underline{H}'_{T+1} = -\infty$. Now suppose $\underline{H}_{T+1}, \underline{H}'_{T+1} > -\infty$, and denote $\underline{H}_{T+1}(\lambda)$ and $\underline{H}'_{T+1}(\lambda)$ as the solution of $\mathcal{F}(H) = \lambda_T$ and $\mathcal{F}'(H) = \lambda_T$ respectively. Similar to the proof that $\underline{H}_3 < \underline{H}'_3$, we have

$$\underline{H}_{T+1}(\lambda_T) \leq \underline{H}_{T+1}(\lambda'_T) < \underline{H}'_{T+1}(\lambda'_T).$$

and the result follows. Similar arguments also prove that $\underline{H}_t < \underline{H}'_t$ for all $t \geq 3$ when $\mathcal{F}(H) > \mathcal{F}'(H)$ for all H .

I now prove the second part of the Proposition where $s'_p < s_p$. Note that using the same arguments in the proof of the first part, if there exists some t such that $\underline{H}'_t < \underline{H}_t$, we should have $\underline{H}'_{t'} < \underline{H}_{t'}$ for all $t' > t$. It implies that when $s_p < s'_p$ and $\underline{H}_2 < \underline{H}'_2$, we either have case 2(a) or case 2(b) in the proposition. In the following, I provide in the following examples for the two cases 2(a) and 2(b). First, when $\underline{H}_2 < \underline{H}'_2$ and $\underline{H}_3 = -\infty < \underline{H}'_3$ (for example when D_n^2 is large), case 2(a) obviously hold. Second, when $\underline{H}_2 + \epsilon = \underline{H}'_2 > -\infty$ for some very small ϵ , $D_n^t = D_n'^t$ and $\underline{H}_3 > -\infty$, case 2(b) holds. $\square$

A.6 Proof of Proposition 4

Proof. Similar arguments in Lemma 1 and Proposition 1 show that the diffusion pattern is characterized by a decreasing sequence of threshold $\underline{H}_t$, which is the solution (if it exists, and otherwise equals to $-\infty$) of

$$s_p \frac{s \sum_{t'=0}^{t-1} \sum_{j \in D_n^{t'}} (v_H - \underline{H}_t)}{v_L - \underline{H}_t} = s \left[\sum_{t'=0}^{t-1} \left(\gamma \left(\frac{N}{G} - 1 \right) + (D_c^{t'} - \frac{N}{G}) \right) \right] + t - 1. \quad (6)$$

I prove the Proposition by induction. First, note that D_c^0 , D_c^1 and D_n^1 do not change with γ . As the left hand side of Equation (6) increases in $\underline{H}_t$ and the right hand side increases in γ , $\underline{H}_2$ increases in γ . Now suppose $\underline{H}_t$ increases in γ for all $t = 3, \dots, T$. First, it implies that D_c^t increases in γ and D_n^t decreases in γ for all $t = 3, \dots, T$, and the right hand side of Equation (6) increases in γ and the left-hand side decreases in γ . Moreover, as the left hand side of Equation (6) increases in $\underline{H}_{T+1}$, $\underline{H}_{T+1}$ increases in γ . The result follows. $\square$

A.7 Proof of Proposition 5

Proof. I first prove the first bullet point of the Proposition. First recall that we have for social network $(s_{N_k})_{k=1}^G$, $U_i^t(p_n) > U_i^t(p_c)$ if and only if

$$s_p \sum_{t'=0}^T \sum_{j \in D_n^{t'}} s_j (v_H - H_i) > \sum_{t'=0}^T \left[s_j (D_c^{t'} - 1) + 1 \right] (v_L - H_i)$$

Multiplying both sides of the Equation by z gives:

$$\begin{aligned} s_p \sum_{t'=0}^T \sum_{j \in D_n^{t'}} s'_j(v_H - H_i) &> \sum_{t'=0}^T \left[s'_j(D_c^{t'} - 1) + z \right] (v_L - H_i) \\ &> \sum_{t'=0}^T \left[s'_j(D_c^{t'} - 1) + 1 \right] (v_L - H_i) \end{aligned}$$

Thus, fixing all other other parameters and if $(D_n^t)_{t=1}^T = (D_n^{t'})_{t=1}^T$, if an individual adopts the new product with social network $(s_{N_k})_{k=1}^G$, he also adopts the new product with social network $(s'_{N_k})_{k=1}^G$. The result follows with inductive arguments similar to the proof of Lemma 2.

Now I prove the second bullet point of the Proposition. First, note that when N is large, the impact of self-connection can be ignored and thus $U_i^t(p_n) > U_i^t(p_c)$ if and only if

$$s_p \sum_{t'=0}^{t-1} \sum_{j \in D_n^{t'}} s_j(v_H - H_i) = \sum_{t'=0}^{t-1} \sum_{j \in D_c^{t'}} s_j(v_L - H_i).$$

Then, similar arguments in Lemma 1 and Proposition 1 show that the diffusion pattern is characterized by a decreasing sequence of threshold $\underline{H}_t$, which is the solution of (if it exists, and otherwise equals to $-\infty$)

$$s_p \frac{v_H - \underline{H}_t}{v_L - \underline{H}_t} = \frac{\sum_{t'=0}^{t-1} \sum_{j \in D_c^{t'}} s_j}{\sum_{t'=0}^{t-1} \sum_{j \in D_n^{t'}} s_j} \quad (7)$$

Now consider two social networks $(s_{N_k})_{k=1}^G$ and $(s'_{N_k})_{k=1}^G$ where $\exists k > k'$ such that

$$N_k(s'_{N_k} - s_{N_k}) = N_{k'}(s_{N_{k'}} - s'_{N_{k'}}) > 0.$$

and $s_{N_{k''}} = s'_{N_{k''}}$ for all $k'' \neq k, k'$. First, in periods where individuals in both group k and k' adopt the incumbent product, the right hand-side of Equation (7) and thus the solution $\underline{H}_t$ are the same for the two social networks. In contrast, in periods where k adopts the incumbent product and k' adopts the new product, the right hand-side of Equation (7) is smaller for social network $(s'_{N_k})_{k=1}^G$. As the left hand-side of Equation (7) increases in $\underline{H}_t$, we have $\underline{H}'_t \leq \underline{H}_t$. The result thus follows. $\square$