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Information acquisition and assimilation capacities as determinants of technological niche markets

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ABSTRACT

We present an equilibrium model where the demand side of the market determines the strategic incentives of firms when considering the introduction of technologically superior products (TSPs) and the subsequent dynamic evolution of the market configuration. Market demand is built on conventional features defining the behavior of decision-makers (DMs), who are required to acquire information sequentially about the characteristics describing the products. Firms may signal the introduction of TSPs, though only sufficiently experimental DMs update their beliefs when selecting a product from a firm. That is, technological habits and inertia condition the incentives of DMs to acquire information and select potential products within a market. In particular, the choices made by the DMs will be determined by their capacity to assimilate signals describing the introduction of TSPs and their attitude towards risk. We identify the conditions required for the emergence of technological niche markets allowing firms that signal the introduction of TSPs to thrive.

Introduction

This study analyzes the importance of different demand structures built on consumers' information acquisition and assimilation capacities for technology dynamics. Our research is motivated by a major observation made by Malerba (2007), who stated that "... the insertion of demand in analyzing the relationship between industrial dynamics and innovation is still in its infancy". He then went on to ask for a redefinition of the passive role played by demand in the industrial organization literature Sutton (1998). However, with a few exceptions (Di Caprio and Santos Arteaga, 2014; Tavana et al., 2016b), the literature has generally remained oblivious to this request, even when dealing with demand-related phenomena (Kahraman et al., 2007; Murarka et al., 2019; Shi and Shen, 2019; Wang and Lyu, 2020; Alhawari et al., 2021).

Malerba (2007) emphasized two main demand features as relevant to promoting innovation across industries: the behavior of consumers [endowed with imperfect information regarding novel technological products and habits and inertia towards the products and technologies composing the market] and their absorptive capabilities. We study these qualities in a sequential information acquisition environment that determines the optimal behavior of consumers/decision-makers (DMs) when choosing among distinct types of products comprising multiple characteristics.

The demand side of the market will be built on four conventional features defining the behavior of consumers and their absorptive capabilities.

(i) DMs face an imperfect information environment and must acquire information about the main sets of characteristics defining the products. Information is acquired sequentially, and its total amount is limited to reflect cognitive and pecuniary information processing costs (Bearden & Connolly, 2007; Epstein & Robertson, 2015).

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(ii) Firms may signal the introduction of technologically superior products (TSPs). We will assume that only sufficiently experimental [perfect foresight] DMs update their beliefs when retrieving information and selecting products from the firms (van den Ende & Dolfsma, 2005; Harty, 2010; Gomez et al., 2016; Höflinger et al., 2018).

- Malerba et al. (2003, 2007) defined experimental DMs as those craving the incorporation of novel technologies in current products or searching for entirely new ones in novel demand segments.
- TSPs are products experiencing improvements in a subset of features defining their main characteristics, increasing the expected utility of perfect-foresight DMs. Credibly signaled improvements may be directly observable or require the purchase of the product to be evaluated. A similar intuition regarding the market introduction of technologically advanced products was put forward by Bender (1989) within a managerial environment.

(iii) Inertia and habits about technologies and products constrain the capacity of DMs to shift across markets (Lin et al., 2015; Si and Chen, 2020; Wang et al., 2021). As stated by Malerba et al. (2003), "customers are very sophisticated and won't buy a new model computer unless it is as good as or better than the old model ones" (pg. 8). Thus, a DM's incentives to shift between product markets should be determined by the potential improvements defined upon the characteristics of the existing products.

(iv) The preferences of DMs, together with their absorptive capabilities, determine their incentives to continue acquiring information within a given market (Eng and Quaia, 2009; Chung et al., 2012; Speier-Pero, 2019). The numerical simulations were performed to illustrate that risk-neutral DMs are more prone to retrieve information across market products than risk-averse ones.

We will illustrate how DMs condition the behavior of firms when proceeding sequentially through the different characteristics of the alternatives and deciding whether to focus on the products from a given firm or evaluate those of a direct competitor.

Intuitively, we will consider two firms offering various products comparable across different sets of characteristics. DMs may observe realizations from the products offered by one of the firms while deciding whether to continue checking the products from this firm or performing comparisons with the products offered by a competing firm. Two main strategic scenarios will be analyzed when formalizing the requirements for the emergence of technological niche markets.

- The emergence of a niche market equilibrium within a Nash precommitment setting requires a demand composed of a sufficiently low proportion of perfect foresight DMs, a relatively low signal intensity, and a reasonably large consumer base on the side of the signaling firm.
- Subgame perfection differs considerably, with the signaling firms also requiring a sufficiently low proportion of perfect foresight DMs and issuing signals of relatively low intensity. However, in this case, a reasonably small consumer base is needed for a niche market equilibrium to emerge.

The main differences between both strategic scenarios are substantial and relate directly to the interactions between the types of DMs composing the demand side of the market, the signaling strategies followed by the firms within the supply side, and the relative size of the consumer bases available to evaluate their products.

Information acquisition in online environments

The four features described above are also significant when analyzing the behavior of DMs in online shopping environments. Recent empirical studies based on questionnaires distributed among online consumers across North America and Europe deliver similar findings regarding their purchase intentions, which range from brand loyalty to the influence of third-party reviews. Thus, while firms may expect a proportion of consumers to form a loyal base, there is still ample room for variability and uncertainty in the expected behavior of DMs when facing novel products or substantial modifications to previously existing ones (Dimoka et al., 2012; Al-Samarraie et al., 2017; Lee et al., 2021).

In addition, DMs do not generally perform thorough searches or product comparisons, a feature emphasized by psychologists when analyzing compulsive consumption and regret (Schwartz, 2004; Chen et al., 2009; Tzini and Jain, 2018), and economists when incorporating bounded rationality into their models (Kreye et al., 2012; Lim, 2013). DMs' intent to perform complex searches indicates their limited information processing and assimilation capacities, constraining the subsequent scope of their decisions.

Fig. 1 describes the average number of keywords used per online search query in the United States and Canada in two different periods, 2017 and 2020. Even though most searches consisted of two words in 2020 – improving upon the dominance of one-word queries in 2017 – the three-word limit accounting for over 80% of total searches prevails in 2020. Because DMs click on two links per search query (Jansen et al., 1998; Baeza-Yates, 2005), this feature highlights the limited information acquisition process followed by consumers.

Thus, DMs may face considerable constraints when noticing the enhanced qualities of products or observing – or believing – the signals issued by a firm (Oghazi et al., 2021). In this regard, when incorporating into the analysis the choice volatility triggered by the anonymous reviews available online (Bae and Lee, 2011; Zimmer & Henry, 2017), firms cannot guarantee that their customer base will remain intact as they venture into the introduction of the novel or enhanced technological products.

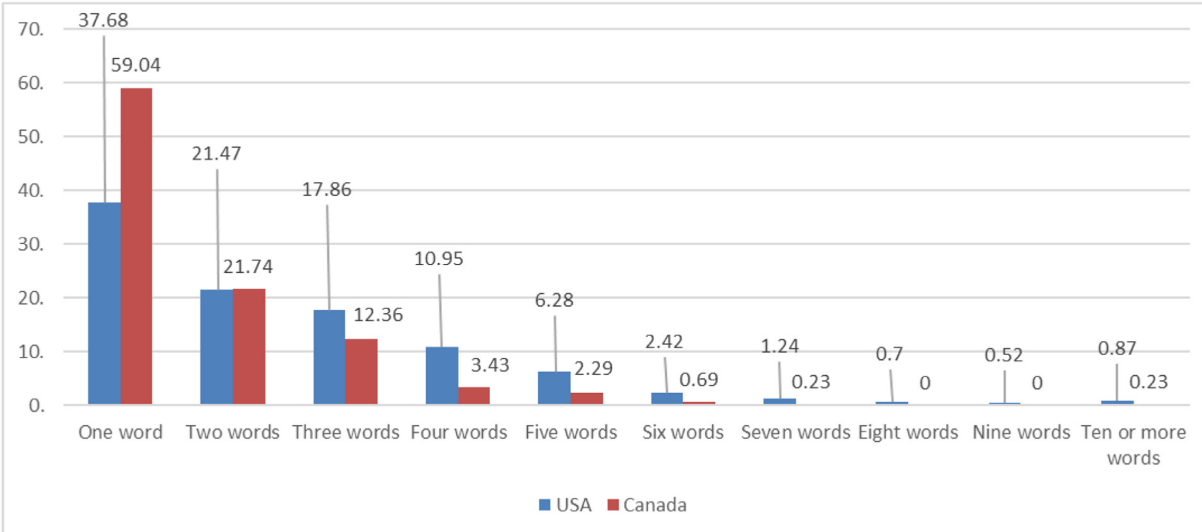
The inherent subjectivity of the DMs' decision processes can also be observed through their answers to different questionnaires describing their consumption habits. For instance, when asking United States consumers

- Whose recommendations are they most likely to trust when choosing between different products online (and allowing for multiple answers)? Most consumers selected their friends, acquaintances, family members (61%), and other customers (53%), while only 39% selected independent review websites.[1]
- Which stage of the digital purchase process makes them happiest? Only 24% selected researching their options, namely, comparing items across sites, while 21% declared selecting products from their website of choice. On the other hand, over 50% chose to see their purchases confirmed and go through checkout.[2]

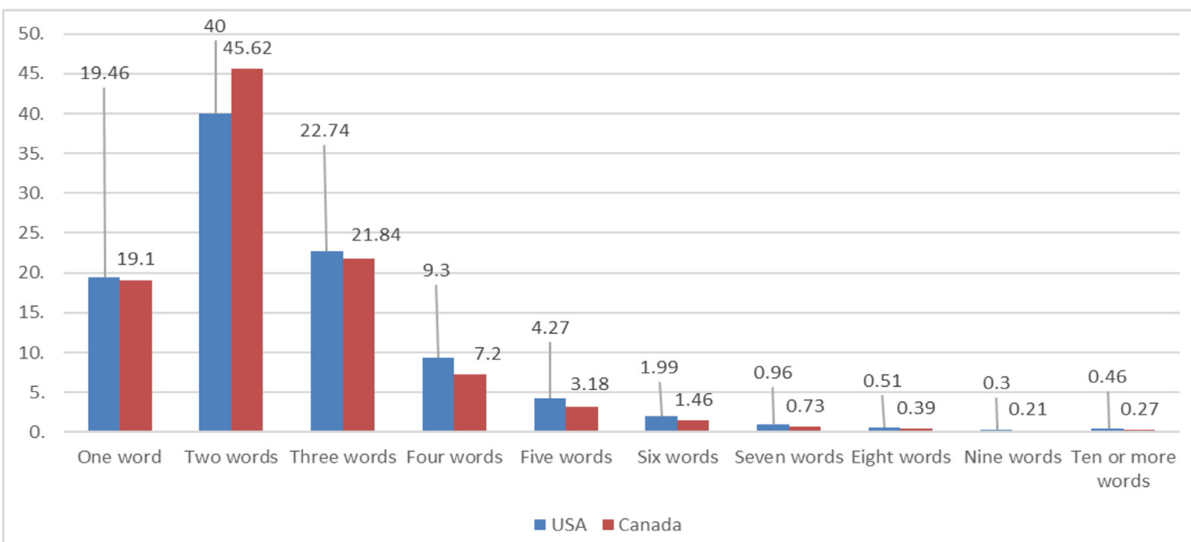
Thus, DMs are divided in their intent to acquire information and display tendencies to implement basic heuristic mechanisms or

[1] Retrieved from Statista (https://www.statista.com/statistics/704847/us-trusted-recommendations-for-online-shopping/). Original source statista.com; Survey period: April 12 to 14, 2017; Region: United States; Number of respondents: 1,052; Age group: 18 years and older; Special characteristics: shop online at least once per year.

[2] Retrieved from Statista (https://www.statista.com/statistics/876031/best-part-of-online-shopping-process-usa/). Original source: emarketer.com; Survey period: May 2018; Region: United States; Number of respondents: n.a.; Age group: 18 years and older.



(a)



(b)

Fig. 1. The average number of search terms for online search queries in the United States and Canada.

perform thorough searches. The volatility of their decisions can also be observed in their payment incentives. When asked what drives them to pay for a higher-priced option when facing similar products online, the answers range from a brand trust (23%) and sufficient product information (9%) to better reviews (35%) and reduced shipping costs (11%).[3]

We conclude by focusing on the behavior of younger consumer groups. When millennial internet users in the United States were asked the likelihood of purchasing products or services using chatbots, only 14% declared not being interested.[4] A similar tendency could be observed among European consumers when asked about their main concerns regarding online purchases. The capacity to inspect the product and retrieve information directly increases in relevance with the consumer group's age sampled.[5] The importance of directly verifiable information describing the main characteristics of products decreases among younger DMs.

Contribution

Given the previous features describing the type of DMs that compose the demand side of the market, we define a game-theoretical framework where duopolistic firms must decide whether or not to signal the existence of a TSP. We will analyze two different types of signaling equilibria determined by the information transmission

[3] Retrieved from Statista (https://www.statista.com/statistics/823936/consumer-reasons-switching-higher-priced-option-online/). Original source: 2018 Consumer Research Report, page 11, conducted by Salsify. Survey period: 2017; Region: United States; Number of respondents: 1,000; Age group: n.a.; Special characteristics: consumers who shopped online at least once in the year.

[4] Retrieved from Statista (https://www.statista.com/statistics/679487/us-millennial-willingness-to-try-chatbot-commerce-2016/). Original source: emarketer.com; Survey period: December 2016; Region: United States; Number of respondents: 500; Age group: 18 to 34 years.

[5] European Commission, (2017). Europeans' attitudes towards cyber security. Special Eurobarometer Report 464a. Question 88, page 42. Survey period: June 2017; Number of respondents: 22,236 internet users. Retrieved fromhttps://ec.europa.eu/commfrontoffice/publicopinion/index.cfm/Survey/index#p=1&instruments=SPECIAL

framework assumed. A Nash equilibrium setting will be applied to oblige each firm to commit to its original signaling strategy. On the other hand, a subgame perfect equilibrium (SPE) will be defined to allow firms to observe the signaling strategy of their rivals and behave accordingly.

The resulting set of equilibria emphasizes the importance that perfect foresight on the side of DMs and the existence of monopolistic rents have for the formation of niche markets that allow firms to signal and introduce TSPs. Moreover, according to the classical findings of Ireland & Stoneman (1986), we will illustrate how the presence of perfect foresight DMs expecting swift technological developments hinders the adoption of the technology available within the market when compared to myopic ones.

The current framework improves upon both the game-theoretical models, mostly centering on the diffusion of technology (Beath et al., 1995; Chen et al., 2018; Zhang & Sun, 2020), and the traditional decision-theoretical ones where demand is based on stopping criteria that validate or dismiss the introduction of new technology (Jensen, 1982; McCardle, 1985). At a formal level, the lack of interaction between the strategic diffusion of innovations by firms and the subsequent emergence of demand by DMs represents a drawback that the equilibrium model developed in the current paper helps to solve (Kim Wang and Seidle, 2017; Li et al., 2020; Ren et al., 2021; Tiberius et al., 2021).

We describe the main results intuitively and highlight the requirements that need to be satisfied for the corresponding equilibria to exist. Technical analyses illustrating these requirements as a function of the set of parameters conditioning firms' behavior through the pre-commitment and subgame perfection frameworks have been relegated to the Appendix sections.

Demand

We build on the models of Di Caprio et al. (2014, 2016) to introduce a demand evaluation and decision environment defined via two expected utilities. These functions are non-recursive and require DMs to redefine their behavior at each stage of the information retrieval process, preventing the implementation of standard dynamic programming techniques.

Product attributes: formalization and technical assumptions

Denote the set of available products as G. Assume that products are given by pairs of characteristics (x_1, x_2), whose values are defined within the Cartesian product of two nonempty sets, $X_1 \times X_2$.

Identifying and evaluating product attributes is a complex task even when the characteristics are directly observable (Lu et al., 2008; Arruda-Filho and Lennon, 2011). Given the coexistence of immediately observable (search) and time-consuming (experience) attributes within a product Nelson (1970), we will assume that both of them can be found in the sets of characteristics composing each X_i, $i = 1, 2$. These temporal requirements are reflected in the information acquisition capacity of DMs, who focus on either fully observing a product, which may or may not be purchased, or partially observing two products and deciding whether or not to purchase the best one.

Two important remarks follow. First, we must highlight that if we were to introduce the convolution of several random variables by assuming that multiple features are included within both X_1 and X_2, and normalizing the corresponding realizations, the main retrieval setting and analyses would remain qualitatively unchanged. An intuitively manageable analytical framework would require limiting the analysis to three features per characteristic, allowing for products to be defined by six main features categorized in two sets of characteristics of the same cardinality. Second, the order defining the sets of characteristics corresponds to the relative importance allocated by the DM. We will elaborate further on this second point in the next section.

A *preference relation* __\succ on X_i, $i = 1, 2$, is a binary relation on X_i satisfying reflexivity, completeness, and transitivity. A function $u_i : X_i \to R$ is a *utility function representing* __\succ *on* X_i if

$$\forall x', x'' \in X_i, \quad x' \_\_ \text{\succ} \ x'' u_i(x') \geq u_i(x'') \Leftrightarrow$$

X_1 and X_2 will be identified with a closed real subinterval of $[0, +\infty)$, that is, for $i = 1, 2$:

$$X_i = \left[x_i^m, \ x_i^M\right], \tag{2}$$

with $0 < x_i^m < x_i^M$ (Wilde, 1980).

We assume X_i to be endowed with the standard Euclidean topology and the preference relation defined by the DM on X_i to be the standard linear order <. Therefore, u_i can be assumed strictly increasing and continuous, implying that the function $u(x_1, x_2) = u_1(x_1) + u_2(x_2)$, defined $\forall (x_1, x_2) \in X_1 \times X_2$, induces an *additive* preference on $X_1 \times X_2$ and is also increasing Wakker (1989).

X_i will also be interpreted as a continuous random variable and $\mu_i : X_i \to [0, 1]$ defined as its associated density function. Given $Z_i \subseteq X_i$, $\mu_i(Z_i)$ represents the subjective probability of the event "the i-th characteristic of a randomly observed product from G is described by a value $x_i \in Z_i$". The support of μ_i is the set $\xi(\mu_i) \stackrel{def}{=} \{x_i \in X_i : \mu_i(x_i) \neq 0\}$. The probability functions μ_i, $i = 1, 2$, will be considered independent, though the decision framework is designed to allow for correlations between both sets of characteristics.

Finally, the *certainty equivalent* defined by μ_i and u_i will be used by the DM as the main point of reference for both sets of characteristics. For $i = 1, 2$, the certainty equivalent of μ_i and u_i is defined as the value $ce_i = u_i^{-1}(E_i)$, with E_i standing for the expected value of u_i. The value ce_i exists and is unique since u_i is assumed to be continuous and strictly increasing.

Expected utility functions from acquiring information

G consists of two potentially different types of products about which the DM can collect information. Let J and K denote the two types of products. Since we are assuming that the DM evaluates two sets of attributes, after the initial characteristic of J is observed, he must determine whether to continue acquiring information on J or to shift his attention to a different type of product K. This decision is based on the realization $x_1 \in X_1$ retrieved from J. We follow Tavana et al. (2016a, 2016c) to introduce the next functions, whose values describe the utilities expected to be obtained from the information acquired on the first characteristic.

Let $F : X_i \to R$ and $H : X_1 \to R$ be given by:

$$F(x_1) \stackrel{def}{=} \int_{P^+(x_1)} \mu_2(x_2)(u_1(x_1) + u_2(x_2))\, dx_2 + \int_{P^-(x_1)} \mu_2(x_2)(E_1 + E_2)\, dx_2 \tag{3}$$

$$H(x_1) \stackrel{def}{=} \int_{Q^+(x_1)} \mu_1(y_1)(u_1(y_1) + E_2)\, dy_1 + \int_{Q^-(x_1)} \mu_1(y_1)(\max\{ u_1(x_1), \ E_1\} + E_2)\, dy_1 \tag{4}$$

such that $\forall x_1 \in X_1$:

$$P^+(x_1) = \{ x_2 \in \xi(\mu_2) : u_2(x_2) > E_1 + E_2 - u_1(x_1)\} \tag{5}$$

$$P^-(x_1) = \{ x_2 \in \xi(\mu_2) : u_2(x_2) \leq E_1 + E_2 - u_1(x_1)\} \tag{6}$$

$$Q^{+}(x_1) = \{ y_1 \in \xi(\mu_1) : u_1(y_1) > \max\{ u_1(x_1),\ E_1\}\} \tag{7}$$

$$Q^{-}(x_1) = \{ y_1 \in \xi(\mu_1) : u_1(y_1) \le \max\{ u_1(x_1),\ E_1\}\}. \tag{8}$$

$F(x_1)$ [resp., $H(x_1)$] describes the gain in expected utility relative to $E_1 + E_2$ in the case when, after evaluating the initial characteristic x_1 of J, the DM decides to observe the second characteristic of J [resp., the first characteristic of K].

Consider a standard evaluation interval framework defined on the characteristics of the products, such as the ones that can be found on online recommender websites such as Tripadvisor, Trivago, and Amazon. The relative importance assigned to the different characteristics can be incorporated into the analysis by assuming that one of the probability distributions provides a higher expected value. Thus, within a common upper limit reference setting, we increase the lower limit of the interval defining the domain so as to increase the expected value that the DM assigns to the potential realizations from the first characteristic. That is, given two probability distributions $\Gamma(x_1)$ and $\xi(x_2)$, and a nondecreasing function $u : \mathrm{R} \to \mathrm{R}$, the domain of the relatively more important characteristic will be shrunk so that

$$\int_{x_1^m}^{x_1^M} u(x_1) d\Gamma(x_1) \ge \int_{x_2^m}^{x_2^M} u(x_2)\, d\xi(x_2), \tag{9}$$

where $E_1 > E_2$, with $x_1^M = x_2^M$. Intuitively, given the relatively higher importance assigned to the first characteristic, we assume that the DM constraints the search to products that score higher than a minimum reference value while discarding the others.

The Appendix A section illustrates the behavior of the functions $F(x_1)$ and $H(x_1)$ within the evaluation intervals $[x_1^m, x_1^M]$ and $[x_2^m, x_2^M]$, such that $x_1^M = x_2^M$ and $E_1 > E_2$ as $x_1^m > x_2^m$, and discusses the natural conditions required for the existence of a crossing point between both functions located below the certainty equivalent value of the first characteristic, i.e., $x_1 < ce_1$.

This latter result constitutes an important contribution to the current paper. Consider two DMs, a standard one basing his information retrieval behavior on the certainty equivalent value assigned to the set of potential realizations of the characteristics and a forward-looking one formalized through Eqs. (3) and (4). Appendix A illustrates how forward-looking risk-neutral or risk-averse DMs are more willing to continue evaluating the initially observed alternatives than standard ones.

Signals and learning

Firms can issue credible signals regarding improvements implemented on X_2, modifying the probability density and expected utility assigned to the corresponding set of products (Brockhoff & Rao, 1993). Note that signals are defined on characteristics that are not initially observable, requiring the consumption of the product to be verified. In this regard, the formal analyses performed throughout the paper can be expanded to analyze the effects of signaling improvements on either X_1 or both characteristics simultaneously (Tavana et al., 2016b).

Improvements are not assumed to be completely radical but enhancements of the secondary characteristics defining the products. The main results described are independent of this assumption. They can also be obtained when considering enhancements of the first set of characteristics, as the analysis performed in Appendix B is emphasized.

We will assume that the DM does not have any initial information on the distribution of characteristics and, as a result, assigns uniform densities to X_1 and X_2, reflecting the highest information entropy faced by the DM. That is, for $i = 1, 2$, the DM defines an initial density function μ_i as $\mu_i(x_i) = \frac{1}{x_i^M - x_i^m}$, $\forall\, x_i \in X_i = [x_i^m,\ x_i^M]$.

Suppose that, after checking the first characteristic, a positive signal is received. Then, the DM must update the density function μ_2 initially defined on X_2.

We will use the symbol θ to denote the fact that positive signals are received and write $\theta = 1$ to indicate that one positive signal is received. Receiving a positive signal, $\theta = 1$, modifies the initial density on X_2, $\mu_2(x_2) = \frac{1}{x_2^M - x_2^m}$ for $x_2 \in [x_2^m,\ x_2^M]$, leading to the following conditional density function:

$$\pi(\theta|x_2) = \begin{cases} \dfrac{3}{2(x_2^M - x_2^m)}\ if x_2 \in \left(\dfrac{x_2^m + x_2^M}{2}, x_2^M\right] \\ \dfrac{1}{2(x_2^M - x_2^m)}\ if x_2 \in \left[x_2^m, \dfrac{x_2^m + x_2^M}{2}\right] \end{cases} \tag{10}$$

That is, half the probability mass from the lower half of the density is shifted to the upper half. The signal leads the DM to update his initial beliefs, $\mu_2(x_2)$, by implementing Bayes' rule as follows

$$\mu_2(x_2|\theta = 1) = \frac{\pi(\theta|x_2)\mu_2(x_2)}{\int_{X_2} \pi(\theta|x_2)\mu_2(x_2)dx_2} \tag{11}$$

Equations (B1) to (B4) within the Appendix B section generalize the conditional density and subsequent Bayesian updating functions presented in Eqs. (10) and (11) so as to account for any potential probability mass shift defined on X_2.

Tavana et al. (2014) illustrate that $F(x_1|\theta = 1) \ge F(x_1)$ and $H(x_1|\theta = 1) \ge H(x_1)$ if $\mu_2(x_2|\theta = 1)$ first-order stochastically dominates $\mu_2(x_2)$.

The framework of analysis just described allows us to categorize the DMs that comprise the market demand in two main groups.

Definition 2.1. We say that "signaling an improved characteristic is technologically neutral" whenever $E_{(2|\theta=1)} = E_2$, while "signaling an improved characteristic is not a technologically neutral strategy" whenever $E_{(2|\theta=1)} > E_2$.

We define as *myopic* those DMs whose E_2 remains unchanged after observing a positive signal – from either credible online recommender systems or independent product reviewers –. As a result, the corresponding functions $F(x_1)$ and $H(x_1)$ remain unaffected whenever TSPs are introduced in the market. If DMs have *perfect foresight*, then observing a credible signal leads to an update of their expectations, such that $E_{(2|\theta=1)} > E_2$, resulting in an upper shift of their functions $F(x_1)$ and $H(x_1)$.

Technological improvement

Two decision processes will condition the technological transition between coexisting markets. Each process determines the potential improvements that signaling firms can guarantee upon the initial characteristic observed by the DMs when deciding whether or not to shift markets.

Irreversible decision processes

Shifting to the signaled market constitutes an irreversible decision (ID) for the DM, who, after observing the initial characteristic of a product in the unsignaled market, must start over in the signaled one. As a result, his final choice, if any, is determined by the set of products composing the signaled market. The resulting $H(x_1|id)$ function provides the expected value from observing a product better than the certainty equivalent to one defined in the signaled market.

$$H(x_1|id) \stackrel{def}{=} \int_{ce_1}^{x_1^M} \mu_1(y_1)\Big(u_1(y_1) + E_{(2|\theta=1)}\Big)dy_1 + \int_{x_1^m}^{ce_1} \mu_1(y_1)\Big(E_1 + E_{(2|\theta=1)}\Big)dy_1. \tag{12}$$

In the above equation and henceforth, the notation *id* refers to the ID setting.

If signaling is not a technologically neutral strategy, then $\frac{\partial H(x_1)}{\partial E_2} > 0$, which implies $H(x_1|id) > H(x_1),\ \forall x_1 \leq ce_1$. We will illustrate numerically how this effect is not sufficient to guarantee a shift of the DM to the signaled market. The loss in utility derived from the irreversibility assumption eliminates the transition incentives that follow from a higher value of E_2 for large x_1 realizations.

Guaranteed improvement processes

In this setting, the signaling firm guarantees the DM a product whose first characteristic value is not inferior to the one from the product assessed within the unsignaled market, that is, $x_{(1|\theta=1)} \geq x_1$.If DMs trust the commitment of the firm, the function $H(x_1|gi)$ would be defined as follows:

$$H(x_1|gi) \stackrel{def}{=} \int\limits_{Q^+(x_1)} \mu_1(y_1)\Big(u_1(y_1) + E_{(2|\theta=1)}\Big)\,dy_1 + \int\limits_{Q^-(x_1)} \mu_1(y_1)\Big(\max\{\,u_1(x_1),\ E_1\} + E_{(2|\theta=1)}\Big)\,dy_1. \tag{13}$$

In the above equation and henceforth, the notation *gi* refers to the GI setting.

Given $E_{(2|\theta=1)} > E_2$, the value of $H(x_1|gi)$ is higher than the corresponding value of $H(x_1)$ defined in the unsignaled market $\forall x_1 \in X_1$.

Numerical simulations

We simulate numerically both the ID and guaranteed improvement (GI) scenarios to study the behavior of the crossing points, i.e., incentive thresholds, defined by the corresponding functions F and H.

Through this section, $X_1 = [5, 10]$ and $X_2 = [0, 10]$ represent the domains on which both sets of characteristics are defined. These specific domains have been chosen to illustrate numerically the main results derived from the current decision theoretical framework. The results build on the natural conditions described in Appendix A, which are required to ensure the existence of a unique threshold value lower than ce_1 within the unsignaled reference setting.

In particular, consider the framework of analysis defined by the evaluation intervals $[x_1^m, x_1^M]$ and $[x_2^m, x_2^M]$ with

- identical upper limits $x_1^M = x_2^M$;
- identical utilities defined on both characteristic spaces;
- a uniform distribution assigned to each interval to reflect the uncertainty faced by DMs;
- $x_1^m > x_2^m$, implying that the first set of characteristics delivers a higher expected utility than the second one;
- $x_1^m \leq ce_2$, limiting the importance assigned to the first characteristic relative to the second one.

Two main constraints are imposed within the above evaluation framework to guarantee the existence of a unique crossing point located below ce_1 when dealing with risk-neutral DMs

- $P^-(x_1^M) \neq \emptyset$: DMs must be willing to observe the second characteristic of a product; that is, the first one cannot guarantee a sufficiently high utility on its own relative to a random choice.
- $x_2^m = 0$: the lower limit value assigned to the second characteristic equals zero.

These requirements represent scenarios where the main characteristics of a product are evaluated within common reference intervals, and DMs focus on those alternatives whose preferred characteristics are distributed above a subjectively determined x_1^m

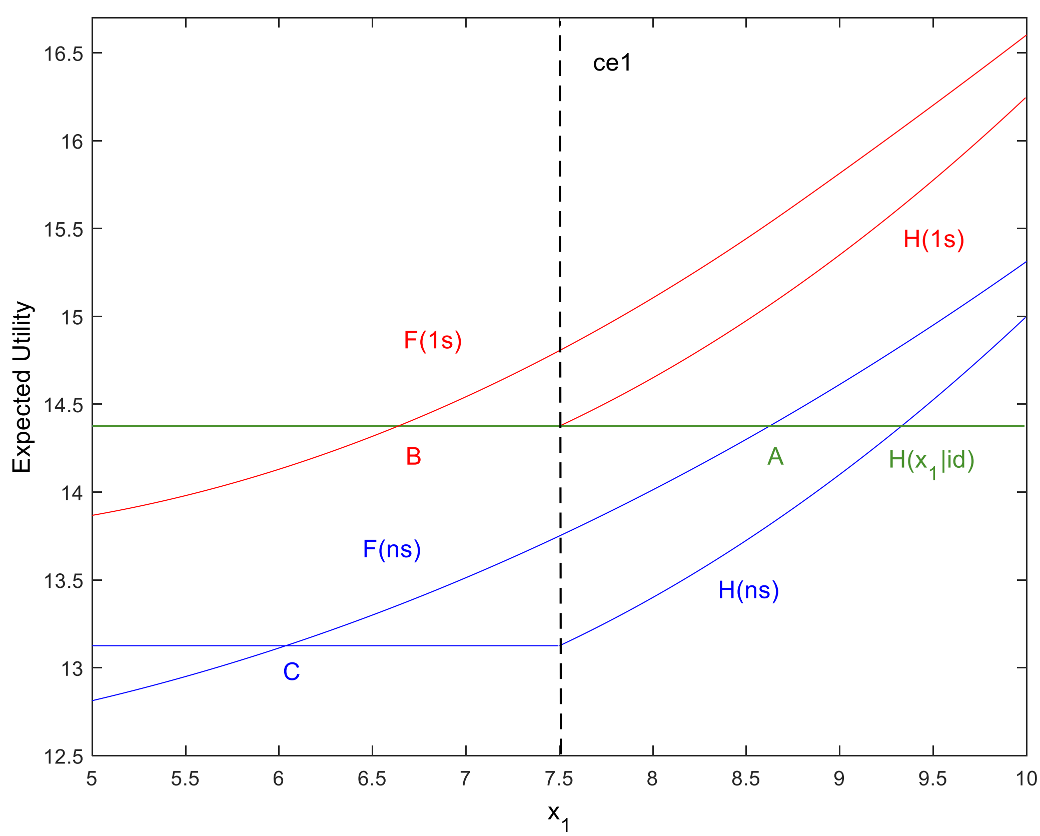


Fig. 2. Optimal threshold values for risk-neutral DMs.

value. Risk-averse DMs require additional formal constraints, restricting even the type of utility function assumed and its concavity.

Fig. 2 describes the “1s” case where one signal indicating the existence of TSPs is issued by one of the firms within a risk-neutral framework, i.e., $u_1(x_1) = x_1$, $u_2(x_2) = x_2$. Points C and B represent the unsignaled and one signal threshold values, respectively. The definition of the Nash pre-commitment equilibria is based on these two reference points. We have used the notation $F(ns)$ and $H(ns)$ to emphasize the fact that the functions $F(x_1)$ and $H(x_1)$ refer to the unsignaled setting.

At the same time, when studying SPE, perfect foresight, DMs will be allowed to shift markets after retrieving information from the firms located in any of them. Similar to the Nash pre-commitment scenario, the cutoff value B defines a GI relative to C, while A accounts for the ID process. In this latter case, the observation forgone when shifting between markets leads $H(x_1|id)$ to a lower expected utility than $H(x_1|gi)$ for all $x_1 > ce_1$ values.

Fig. 3 shows the threshold points relative to the same environment as Fig. 2 when DMs are risk-averse, i.e., $u_1(x_1) = \sqrt{x_1}$, $u_2(x_2) = \sqrt{x_2}$. Note how risk-averse perfect foresight DMs require lower realizations of x_1 than risk-neutral ones to continue acquiring information on the initial products. Moreover, in both the risk-neutral and risk-averse cases, GI does not imply faster adoption of the TSP, as can be inferred from the rightward shift of the corresponding threshold values, i.e., from point C to B.

Supply

Through this section, we demonstrate that the strategic decision to signal the existence of a TSP is conditioned by the type of DMs composing the demand side of the market.

Technological transition

Consider a duopolistic environment with identical firms. Each firm must decide between either introducing a TSP and issuing the corresponding signal, S, or remaining in the unsignaled market, NS. The time sequence defining the strategic environment proceeds as follows. There are three time periods, $t = 0, 1, 2$. Signals can only be issued at $t = 0$ or $t = 1$. The DM acquires information during periods $t = 1$ and $t = 2$. Thus, the strategies of the firms aim at modifying the information acquisition process of DMs at $t = 0$ and $t = 1$.

In order to avoid biases in the final choice made by the DM, we will assume that if the product(s) observed after completing the information acquisition process does(do) not provide him with an expected utility higher than $E_1 + E_2$, then the DM rejects making a random choice (Christensen, 1997; Dedehayir et al., 2014; Di Caprio & Santos Arteaga, 2014).

As in Rahman & Loulou (2001), we will analyze two different strategic equilibria determined by a specific information transmission framework. A *Nash pre-commitment equilibrium* is considered whenever a firm cannot monitor the rival decisions and must therefore commit to the signaling strategy followed at $t = 0$. *Subgame perfection* implies that a firm is allowed to monitor the interim signals issued by its rivals before deciding whether or not to issue a signal. As a result, firms should anticipate the signaling decision of the rival and incorporate it when defining their signaling strategies at $t = 0$.

Nash pre-commitment equilibrium

Consider the threshold values described in Figures 2 and 3. For $\varepsilon = B, C$, denote by $r(\varepsilon)$ and Rev_ε the revenue and expected revenue per firm when both of them compete in a duopoly within the ε

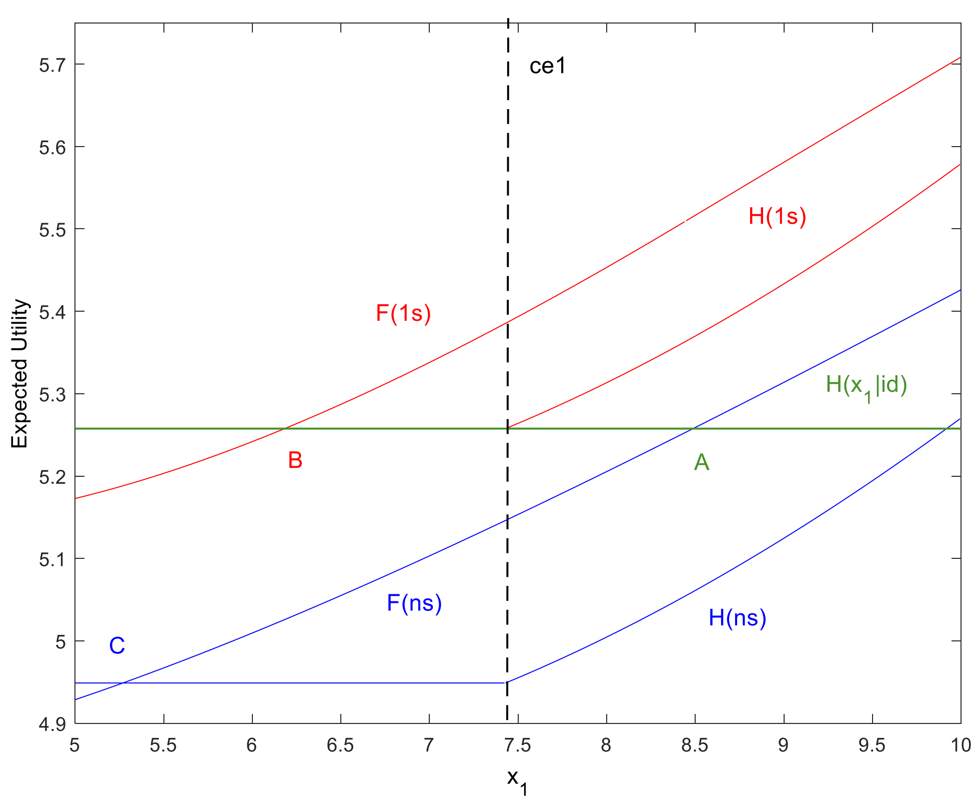


Fig. 3. Optimal threshold values for risk-averse DMs.

setting. Similarly, $Rev_{B|s}$ and $Rev_{C|ns}$ are the expected revenues of the unilaterally signaling and not signaling firm, respectively.

The signaling strategies that can be implemented by the firms within a pre-commitment environment give rise to a technological transition matrix (TTM) whose rows and columns represent the strategies of the firm and its rival, respectively. This matrix is defined as follows:

	S	NS
S	Rev_B, Rev_B	$Rev_{B\|s}, Rev_{C\|ns}$
NS	$Rev_{C\|ns}, Rev_{B\|s}$	Rev_C, Rev_C

Intuitively speaking, when both firms signal the introduction of a technological improvement, they must compete for DMs in the corresponding market. This yields an expected revenue, Rev_B, strictly smaller than the one derived by the signaling firm, $Rev_{B|s}$, in a monopolistic setting. Moreover, given the fact that perfect foresight DMs shift to the signaled market, the not signaling firm, which receives $Rev_{C|ns}$, would suffer a loss with respect to the revenue obtained in the not signaling equilibrium, Rev_C. Despite the decrease in competition induced, signaling unilaterally leads perfect foresight DMs to require a higher continuation value. Thus, the relative strength of these effects on the revenues expected to be obtained determines the signaling incentives of firms.

We refer to $\varphi(f)$ as the probability that firms assign to DMs gathering information from any of their products within a duopolistic competing scenario. The corresponding probability assigned to the rival firm equals $\varphi(f^r) = 1 - \varphi(f)$. To simplify notations, we will use ε to denote both the value of the threshold and its projection on X_1.

Given the threshold values described in the numerical simulations, the expected revenue of a firm when competing with a rival at ε, with $\varepsilon = B, C$, is given by the following expression:

$$Rev_\varepsilon = \varphi(f)\left[\gamma(\varepsilon) r_\pi(\varepsilon) + \left(1-\gamma(\varepsilon)\right)[\varphi(f)\gamma(ce_1)r]\right] + \varphi(f^r)\left[\left(1-\gamma(\varepsilon)\right)[\varphi(f)\gamma(ce_1)r]\right], \tag{14}$$

where

- $\gamma(\varepsilon) = \frac{(x_1^M - \varepsilon)}{(x_1^M - x_1^m)}$, with $\varepsilon = A, B, C$, is the probability that the DM continues acquiring information on the initial product observed;
- $r_\pi(\varepsilon) = \sigma\left(P^+(x_1)\right) r$, is the revenue expected by the firm when $x_1 > \varepsilon$, with $\varepsilon = A, B, C$;
- $\sigma\left(P^+(x_1)\right) = \int_{x_1}^{x_1^M} \left(\frac{x_2^M - x_2(x_1)}{x_2^M - x_2^m}\right) dx_1$, represents the probability of the DM observing $u_2(x_2) > E_1 + E_2 - u_1(x_1)$.
- r is the revenue obtained by the firm from the sale of its product.

Remarks. . (1) Regarding the definition of $\sigma\left(P^+(x_1)\right)$, the exact expression, accounting for the whole set of potential probability mass shifts defined on X_2, is developed through Equations (B1) to (B11) within the Appendix B section.
(2) The case where $\varepsilon = A$ is not considered in this section since it is not relevant within the current pre-commitment scenario. The analysis of this case requires further assumptions and explanations and will be examined in detail within the SPE setting. □

Eq. (14) can be rewritten as

$$Rev_\varepsilon = \varphi(f)\, r \left[\gamma(\varepsilon)\sigma\left(P^+(x_1)\right) + \left(1-\gamma(\varepsilon)\right)\gamma(ce_1)\right]. \tag{15}$$

When describing the expected revenue derived from a unilateral signaling framework the presence of both DMs, perfect foresight and myopic within the set of potential consumers, must be explicitly incorporated into the analysis (Liu et al., 2017). As a consequence, the unilaterally signaling firm would receive an expected revenue given by:

$$Rev_{B|s} = \alpha\varphi(f)\, r\left[\gamma(C)\sigma\left(P^+(x_1)\right) + \left(1-\gamma(C)\right)\gamma(ce_1)\right] + (1-\alpha)\, r\left[\gamma(B)\sigma\left(P^+(x_1)\right) + \left(1-\gamma(B)\right)\gamma(ce_1)\right] \tag{16}$$

where α stands for the percentage of myopic DMs composing the market demand. This expression follows from the fact that perfect foresight DMs search only within the signaled market. When a unique firm issues signals, it competes in terms of the threshold C for the α percentage of myopic DMs with the firm that does not signal. At the same time, the signaling firm serves alone the $(1-\alpha)$ proportion of perfect foresight DMs in terms of the threshold B.

Note that preserving a consistent equilibrium framework requires that the uniform density function defined on X_2, which, at the same time, determines the value of $\sigma\left(P^+(x_1)\right)$, remains unchanged when dealing with myopic DMs. Their inability to assimilate signals prevents myopic DMs from recognizing the superiority of the products introduced by the unilaterally signaling firm. This assumption could be modified, allowing myopic DMs to ascertain the superior quality of the products the signaling firm offers when retrieving information from the corresponding market. Clearly, this modification would foster the signaling incentives of firms. However, it also implies that firms would prefer to deal with myopic DMs when signaling since they would face a threshold value of C – increasing the acceptance probability of their products relative to the B value defined by perfect foresight DMs –. Thus, preserving consistency implies that myopic DMs either do not observe or remain unaffected by the features on which technological improvements are introduced when retrieving information.

On the other hand, when both firms issue signals and a signaling duopoly is defined, we will assume that both types of DMs acknowledge this fact and update the distribution of the second characteristic accordingly when retrieving information. Once all firms introduce a technological improvement within the market, the technology becomes standardized, and all DMs behave according to the updated distribution of characteristics. The model is designed to emphasize the risks the signaling firms face when issuing unilaterally, together with the resulting monopolistic gains. We could assume that both types of DMs prevail within the duopolistic signaling market, driving the expected revenues of the firms accordingly. However, this assumption would increase the complexity of the analysis considerably without adding any relevant insights.

Remark. . We will relax the assumption that perfect foresight DMs search only within the signaled market when studying the SPE version of the game. We will allow for consumption habits and inertia among perfect foresight DMs. Thus, even though perfect foresight DMs recognize the superiority of the products being signaled, they could still acquire information relative to the unsignaled market because of prevailing inertia and consumption habits. It must be emphasized that this assumption does not affect the qualitative results derived from the pre-commitment scenario. □

The expected revenue received by the firm that remains in the unsignaled market equals

$$Rev_{C|ns} = \alpha Rev_C. \tag{17}$$

Clearly, $Rev_{B|s} > Rev_B$ when $\alpha = 0$ and $Rev_{C|ns} < Rev_C$ when $\alpha < 1$. However, any comparison between Rev_B and Rev_C depends on the values of $\sigma\left(P^+(x_1)\right)$ and $\gamma(ce_1)$. That is, if the shifts in the thresholds as signals are issued can be continuously approximated, then

$$\frac{\partial Rev_\varepsilon}{\partial \varepsilon} = \varphi(f)\, r\, \gamma'(\varepsilon)\left[\sigma\left(P^+(x_1)\right) - \gamma(ce_1)\right] \tag{18}$$

with $\gamma'(\varepsilon) < 0$. Exact comparisons between Rev_B and Rev_C are presented throughout the different scenarios analyzed within the Appendix B section, while an analysis of their behavior in an environment with multiple signals can be found in Tavana et al. (2016b).

Myopic decision-makers

Suppose that the whole set of DMs is myopic. As a result, the expected revenues derived by the firms do not depend on their signaling strategies. Indeed, by definition, all entries of the corresponding TTM would be given by Rev_C and random events would drive the transitions between technologies, resulting in identical Nash and SPE.

Furthermore, whenever frictions arise from signaling the introduction of a TSP (i.e., whenever quality decreases as the product is introduced), with a consequent decrease in the expected utility derived from the product (Malerba et al., 2003), any firm issuing signals would not be able to generate a niche market on which to thrive, leading to its eventual disappearance.

Theorem 3.1. Suppose that the whole set of DMs is myopic and frictions arise in the signaled market. Then, the subgame perfect and Nash's pre-commitment equilibria imply that technological transition does not take place.

Proof. . Consider the TTM that follows from a myopic scenario. If the frictions triggered lead to a signaling payoff lower than Rev_C, then both firms coordinate on *NS*, which constitutes a strictly dominant strategy. □

Decision-makers with perfect foresight

Suppose that the whole set of DMs is endowed with perfect foresight, that is, $\alpha = 0$ and $Rev_{C|ns} = 0$. In this case, the relative values of Rev_C and $Rev_{B|s}$ determine the set of Nash pre-commitment equilibria.

Assume first that $Rev_{B|s} > Rev_C$. In this case, signaling at $t = 0$ defines the only Nash pre-commitment equilibrium. The Nash pre-commitment scenario is equivalent to a classical prisoner's dilemma whenever $Rev_B < Rev_C$.

Theorem 3.2. Suppose that the market is composed by perfect foresight DMs and $Rev_{B|s} > Rev_C$. Then, signaling constitutes an optimal strategy independently of the relative values taken by Rev_B and Rev_C.

Appendix B.1 illustrates the results described in Theorem 3.2. In particular, the incentives fostering technological transition weaken as myopic DMs are introduced in the market and firms become endowed with relatively higher $\varphi(f)$ values. That is, the payoff incentives obtained from monopolizing the signaled market lose relative importance as firms expect DMs to evaluate their products with higher probability, increasing their capacity to compete in a duopolistic scenario.

Assume now that $Rev_{B|s} = Rev_C$. Analogously to the previous case, signaling becomes a weakly dominant strategy.

Finally, assume that $Rev_{B|s} < Rev_C$. In this case, a mixed Nash pre-commitment equilibrium is obtained based on the relative values of the matrix entries.

Proposition 3.3. Suppose that all DMs have perfect foresight and $Rev_{B|s} < Rev_C$. Then, the technological transition game (TTG) admits two Nash pre-commitment equilibria in pure strategies, namely, (S, S) and (NS, NS).

Corollary 3.4. Suppose that all DMs have perfect foresight and $Rev_{B|s} < Rev_C$. Then, the TTG has a mixed strategy equilibrium determined by

$$\frac{Rev_C - Rev_{B|s}}{Rev_C + Rev_B - Rev_{B|s}} = \varphi^*(S),$$

where $\varphi^*(S)$ defines the probability of a firm signaling the introduction of a TSP, with $\varphi^*(NS) = 1 - \varphi^*(S)$.

Note that $\frac{\partial \varphi^*(S)}{\partial Rev_{B|s}} < 0$ and $\frac{\partial \varphi^*(S)}{\partial Rev_C} > 0$. Thus, an increase in $Rev_{B|s}$ or a decrease in Rev_C would expand the set of probability values for which signaling constitutes an equilibrium strategy.

A detailed analysis of the requisites guaranteeing that $Rev_{B|s} < Rev_C$ is provided in Appendix B.2. The results presented in this appendix section are based on the fact that the introduction of a TSP product constitutes a risk for the signaling firm, which faces uncertainty regarding the acceptance of the modifications among perfect-foresight DMs. We illustrate how a low signal intensity, namely, a relatively small probability mass shift from the lower to the upper half of the distribution, together with a solid consumer base, favors the prevalence of the mixed strategy equilibrium. These effects are complemented by a relatively high proportion of myopic DMs, implying lower monopolistic revenues. These incentives vanish as the intensity of the signal increases and the relative size of the consumer base of the firm decreases, shifting from a two-equilibria situation to a prisoner's dilemma.

Perfect foresight and myopic decision-makers

Consider now the case where the market is composed of both types of DMs. Perfect foresight consumers, as well as a percentage of the myopic ones, defined via $Rev_{B|s}$ for $\alpha \in (0, 1)$, would select a product from the signaling firm. The expected revenue received by the not signaling firm equals $\alpha Rev_C > 0$. As a result, the set of Nash pre-commitment equilibria is determined by the relative values of Rev_C, Rev_B and $Rev_{B|s}$.

In this regard, note that $Rev_{B|s}$ is obtained considering only the $(1 - \alpha)$ proportion of perfect foresight DMs shifting their information acquisition processes to the signaled market. Thus, if operating within the signaled market would constitute an advantage for the signaling firm, i.e. $Rev_B > Rev_C$, the signaling incentives will be lower than in the perfect foresight scenario.

Note that, besides the Nash pre-commitment equilibria arising within the perfect foresight scenario, the proposed approach fosters the emergence of niche markets where the existence of TSPs is signaled by one firm.

Proposition 3.5. Suppose that the market is composed of both types of DMs – myopic and perfect foresight –, $Rev_{B|s} > Rev_C$ and $Rev_B < Rev_{C|ns}$, the TTG has two Nash pre-commitment equilibria in pure strategies, namely, (S, NS) and (NS, S).

A sufficient condition for the equilibria of Proposition 3.5. to exist is that $Rev_{B|s} > Rev_C > Rev_{C|ns} > Rev_B$. This chain of inequalities holds true if we assume both the value of α to be sufficiently close to zero and the payoff difference between $Rev_{B|s}$ and Rev_B through $(1 - \varphi(f))$ to be large enough. These two assumptions require the market to be composed by a relatively low percentage of myopic DMs and the monopolistic rents received from signaling unilaterally to be sufficiently large compared to those obtained from competing within the signaled market. The relative intensity of $(1 - \varphi(f))$ is indeed what guarantees that $Rev_{B|s}$ is larger than Rev_C and Rev_B.

It should be emphasized that a small value of α is required for the exploitation of the monopolistic revenues relative to the duopolistic ones, $Rev_{B|s} > Rev_B$. At the same time, a relatively high value of α is required for $Rev_{C|ns} > Rev_B$. Appendix B.2.1 analyzes in detail the requisites that must be satisfied for the existence of the equilibrium described in Proposition 3.5. In addition to a relatively large proportion of myopic DMs, sufficiently low signal intensities and large consumer bases are also required to guarantee the existence of this equilibrium.

Note that, as in the perfect foresight setting, a relatively large value of $Rev_{B|s}$ would lead both firms to try to signal first, due to the monopolistic rents delivering $Rev_{B|s} > Rev_{C|ns}$.

Subgame perfection

Consider the TTMs potentially faced by firms at $t = 1$, just before DMs start acquiring information.

	Guaranteed Improvement	
	S	*NS*
S	Rev_B, Rev_B	$Rev_{B|s}, Rev_{C|ns}$
NS	$Rev_{C|ns}, Rev_{B|s}$	Rev_C, Rev_C

	Irreversible Decision	
	S	*NS*
S	Rev_B, Rev_B	$Rev_{A-C|s}, Rev_{C-A|ns}$
NS	$Rev_{C-A|ns}, Rev_{A-C|s}$	Rev_C, Rev_C

The GI setting bears a considerable resemblance to the Nash pre-commitment scenario. In fact, the set of GI equilibria are going to be defined by the relative values of Rev_B, Rev_C, $Rev_{B|s}$, and the α proportion of myopic DMs. However, subgame perfection enhances the capacity of firms to create niche markets at $t = 1$ relative to the pre-commitment case.

Consider now the ID framework. The expected revenue received by the not signaling firm equals

$$Rev_{C-A|ns} = (1-\alpha)[\varphi(f)[\gamma(A)r_\pi(A)] + \varphi(f^r)[(1-\gamma(B))\varphi(f)\gamma(A)r]] + \alpha Rev_C \tag{19}$$

To be consistent, we have required the observation acquired from the unsignaled market to be higher than A in order for the DM to purchase the subsequent product. Even if ce_1 is taken as a reference point instead of A, we have that $Rev_{C-A|ns} < Rev_B$ for $\alpha = 0$, as required to define the perfect foresight subgame equilibria in the next section. See Figures B1 and B7 within the Appendix B section for additional intuition regarding the behavior of $Rev_{C-A|ns}$ and Rev_B.

Similarly, the expected revenue received by the signaling firm equals

$$Rev_{A-C|s} = (1-\alpha)\Big[\varphi(f)\Big[\gamma(B)r_\pi(B) + \Big(1-\gamma(B)\Big)\varphi(f)\gamma(ce_1)r\Big] + \varphi(f^r)\Big[\Big(1-\gamma(A)\Big)\gamma(ce_1)r\Big]\Big] + \alpha Rev_C. \tag{20}$$

Note that *perfect foresight* DMs shift to the signaled market provided that $x_1 < A$ in the unsignaled one. On the other hand, if $x_1 < B$, we have assumed that they could acquire information from the signaled market with probability $\varphi(f)$. These requirements describe the preference for experimentation that must be exhibited by perfect foresight DMs to overcome their initial consumption inertia.

Perfect foresight [$\alpha = 0$] decision-makers

Consider the expected revenues described in the previous section. Three potential TTMs can be defined at $t = 0$.

If $Rev_C > Rev_{B|s}$ and $Rev_C > Rev_{A-C|s}$, then a *NS* strategy from a firm at $t = 0$ leads the rival not to signal at $t = 1$. Similarly, $\alpha = 0$ leads to $Rev_{C|ns} = 0$ and $Rev_{C-A|ns} < Rev_B$, which at $t = 0$ implies

	S	*NS*
S	Rev_B, Rev_B	-
NS	-	Rev_C, Rev_C

The SPE is determined by the relative values of Rev_B and Rev_C, with both firms coordinating their *S* or *NS* strategies.

If $Rev_{B|s} > Rev_C$ in the GI case, then a *NS* strategy from the firm at $t = 0$ implies that the rival will signal at $t = 1$, leading to

	S	*NS*
S	Rev_B, Rev_B	$Rev_{B|s}, 0$
NS	-	-

Thus, both firms will signal the introduction of a TSP at $t = 0$ in the corresponding SPE.

If $Rev_{A-C|s} > Rev_C$ in the ID case, then a *NS* strategy from the firm at $t = 0$ implies that the rival will signal at $t = 1$, leading to

	S	*NS*
S	Rev_B, Rev_B	$Rev_{A-C|s}, Rev_{C-A|ns}$
NS	-	-

The SPE will be determined by the values of Rev_B and $Rev_{C-A|ns}$. Note that the assumptions made when defining $Rev_{C-A|ns}$ and the fact that $\gamma(A) < \gamma(B)$ allow for $Rev_{C-A|ns} < Rev_B$. In this case, a *S* strategy would be the equilibrium strategy of the firm at $t = 0$.

Thus, we can formulate the following propositions. (See Appendixes B.2 and B.3 for an illustration of the results described in Propositions 3.6 and 3.7.)

Proposition 3.6. Suppose that all DMs have perfect foresight, $Rev_{B|s} < Rev_C$ and $Rev_{A-C|s} < Rev_C$. Then, the TTG has a unique SPE given by (NS, NS).

Proof. . If all DMs have perfect foresight, $Rev_{B|s} < Rev_C$ and $Rev_{A-C|s} < Rev_C$, then *NS* constitutes a dominant strategy for the firm and its rival if $Rev_B < Rev_C$. This inequality is guaranteed since $Rev_{B|s} > Rev_B$ and $Rev_{A-C|s} > Rev_B$ (for sufficiently low signal intensities and large consumer bases) when $\alpha = 0$. Thus, $Rev_B < Rev_C$, and *NS* constitutes the unique SPE. □

Proposition 3.7. If all DMs have perfect foresight, $Rev_{B|s} > Rev_C$ and $Rev_{A-C|s} > Rev_C$, the TTG has a unique SPE where the firm and its rival signal.

In this latter case, relatively high signal intensity and a small consumer base are required for the existence of a signaling duopolistic equilibrium.

It should be underlined that, as in the Nash pre-commitment scenario, endowing the whole set of DMs with perfect foresight prevents the emergence of niche markets. Technological transition is completely determined by the expected revenues obtained from signaling unilaterally, i.e., $Rev_{B|s}$ and $Rev_{A-C|s}$. This result follows from the zero and $Rev_{C-A|ns} < Rev_B$ payoffs respectively received by the firm choosing *NS* when the rival signals.

Decision-makers with perfect foresight and myopic [$\alpha \in (0, 1)$]

We start by noting that the set of equilibria described in Section 3.3.1 can be derived within the current scenario. Nonetheless, we focus our attention on the requirements allowing for the emergence of niche markets where firms signaling their innovations may thrive and compare the subsequent equilibria with those obtained in the perfect foresight and pre-commitment settings.

If $Rev_B < Rev_{C|ns}$ in the GI case, then a signaling strategy from the firm at $t = 0$ leads the rival to choose *NS* at $t = 1$. This payoff inequality follows from $\alpha > 0$, which implies that $Rev_{C|ns} > 0$. Moreover, if $Rev_C < Rev_{B|s}$, then a *NS* strategy from the firm at $t = 0$ would lead the rival to signal at $t = 1$. The matrix at $t = 0$ would be given by

	S	*NS*
S	-	$Rev_{B|s}, Rev_{C|ns}$
NS	$Rev_{C|ns}, Rev_{B|s}$	-

As was the case in the Nash pre-commitment scenario, the existence of equilibria leading to the emergence of niche markets entails $Rev_B < Rev_{C|ns}$ and $Rev_C < Rev_{B|s}$. It follows that $Rev_B < Rev_{C|ns} < Rev_C < Rev_{B|s}$. In this case, since $Rev_{C|ns} < Rev_{B|s}$, firms have a clear incentive to signal first and let rivals follow a not signaling strategy.

If $Rev_{A-C|s} > Rev_C$ in the ID case, then a *NS* strategy from the firm at $t = 0$ leads the rival to signal at $t = 1$. Besides, if $Rev_{C-A|ns} > Rev_B$, then a signaling strategy from the firm at $t = 0$ leads the rival to choose *NS* at $t = 1$. As in the GI scenario, this latter inequality builds on the fact that we are assuming $\alpha > 0$. The matrix at $t = 0$ would be defined as follows

	S	*NS*
S	-	$Rev_{A-C|s}, Rev_{C-A|ns}$
NS	$Rev_{C-A|ns}, Rev_{A-C|s}$	-

The set of assumptions made to define $Rev_{C-A|ns}$ together with $\gamma(A) < \gamma(B)$ imply that $Rev_{A-C|s} > Rev_{C-A|ns}$, which leads firms to consider signaling as an optimal strategy at $t = 0$. Therefore, as in the GI scenario, firms have a distinct incentive to signal at $t = 0$ while letting rivals follow a not signaling strategy at $t = 1$. If a firm does not signal at $t = 0$, the rival will, yielding a specialized market niche for TSP.

Note that whenever both types of DMs interact, $Rev_{A-C|s}$ is generally larger than Rev_B and Rev_C. In other words, the largest expected revenues are obtained by the firms that monopolize the signaled markets. The conditions required to obtain this equilibrium give place to the ensuing implications.

(i) For $Rev_{C-A|ns} > Rev_B$, both $Rev_C > Rev_B$ and a sufficiently high value of α are required, since $Rev_{C-A|ns} < Rev_B$ when $\alpha = 0$. Therefore, the existence of a relatively large percentage of myopic DMs implies that the firm that does not signal remains as a follower of the signaled market monopolist. Moreover, competing in the signaled market implies a loss relative to the expected revenue derived from interacting within the unsignaled market.

(ii) For $Rev_{A-C|s} > Rev_C$, $\varphi(f^r)[\left(1-\gamma(A)\right)\gamma(ce_1)r]$ must counteract the relative loss triggered by $\varphi(f)[\gamma(B)\bar{r}_\pi(B) + \left(1-\gamma(B)\right)\varphi(f)\gamma(ce_1)r]$, which follows from the requirement that $Rev_C > Rev_B$. In other words, firms face a relative loss when competing in the signaled market, in contrast to the unsignaled one. On the other hand, a compensating gain is obtained from the constrained capacity of the rival firm to provide DMs with a value of the first characteristic located above A – relative to point C –.

The next set of results follows directly from the previous analysis. Appendixes B.2 and B.2.1 illustrate the results described in Theorem 3.8 and Corollary 3.9, while Appendix B.3 focuses on the results described in Theorem 3.10 and Corollary 3.11.

Theorem 3.8. Suppose that myopic and perfect foresight DMs interact within a GI market scenario, $Rev_B < Rev_{C|ns}$ and $Rev_C < Rev_{B|s}$. Then, the TTG has a SPE resulting in the emergence of a signaling niche market.

Corollary 3.9. Suppose that myopic and perfect foresight DMs interact within a GI market scenario, $Rev_B < Rev_{C|ns}$ and $Rev_C < Rev_{B|s}$. Then, under subgame perfection, both firms are incentivized to signal first and take over the technological niche market.

Theorem 3.10. Suppose that myopic and perfect foresight DMs interact within an ID market scenario, $Rev_C < Rev_{A-C|s}$ and $Rev_B < Rev_{C-A|ns}$. Then, the TTG has an SPE resulting in the emergence of a signaling niche market.

Corollary 3.11. Suppose that myopic and perfect foresight DMs interact within an ID market scenario, $Rev_C < Rev_{A-C|s}$ and $Rev_B < Rev_{C-A|ns}$. Then, under subgame perfection, both firms are incentivized to signal first and take over the technological niche market.

The incentives for the creation of niche markets are the same in both the GI and ID settings. In this sense, the inequalities $Rev_C < Rev_{B|s}$ and $Rev_C < Rev_{A-C|s}$ reflect the importance of the monopolistic rents obtained from signaling unilaterally in the GI and ID cases, respectively. In addition, $Rev_B < Rev_{C|ns}$ and $Rev_B < Rev_{C-A|ns}$ provide the respective incentives precluding further competition from arising in the niche market after a firm signals.

However, both settings differ to a certain extent. In the GI scenario, the signaling incentives provided by monopolistic rents dominate other potential payoffs, i.e., $Rev_B < Rev_{C|ns} < Rev_C < Rev_{B|s}$. The status quo payoff defined by Rev_C imposes a loss on the firms that do not signal within the technological niche market. This loss should incentive the introduction of TSPs through niche markets triggered by the existence of monopolistic rents that arise from signaling unilaterally.

In the ID scenario, a similar type of reasoning requires $Rev_C > Rev_{C-A|ns}$. A sufficient condition for this inequality to hold true is that $\left(1-\gamma(C)\right) > \varphi(f^r)\left(1-\gamma(B)\right)$. If this were not the case, firms not issuing a signal would benefit from the creation of the niche market, as their revenues would increase relative to the initial duopolistic status quo. However, they would still have a clear incentive to signal ahead of the rival, since, as illustrated through this section, $Rev_{A-C|s} > Rev_{C-A|ns}$.

Managerial implications

The limit imposed on the set of characteristics considered and information retrieved by DMs follows the constraints inherent to their assimilation capacities, either cognitive or pecuniary. DMs may evaluate the main characteristics of the products offered by both firms and make a partially informed decision or perform a complete assessment of one of them and then make the corresponding decision. Clearly, some uncertainty will always prevail due to the very own nature of the products and the cognitive retrieval processes. These features condition the signaling behavior of firms when deciding how to proceed within the resulting strategic environment.

The existence of a niche market equilibrium within the Nash pre-commitment and GI subgame perfect settings requires a sufficiently large proportion of myopic DMs, together with a relatively low signal intensity and a sufficiently large consumer base on the side of the signaling firm. The results obtained illustrate how the introduction of a TSP represents a risk for the signaling firm, given the uncertainty faced when considering the acceptance of the modifications implemented by perfect-foresight DMs. Signaling firms limit the risk derived from the introduction of TSPs through low signal intensity and a solid consumer base. These effects are complemented by a relatively high proportion of myopic DMs, further limiting the potential risks derived from the introduction of TSPs.

These incentives differ significantly when considering an irreversible SPE. In this case, a sufficiently large proportion of myopic DMs and a relatively low signal intensity are also required. However, signaling firms should be endowed with a sufficiently small consumer base to foster the emergence of a technological niche market. This latter requirement follows from the stricter evaluation constraint imposed on non-signaling firms within the SPE environment, requiring them to provide DMs with a value of the first characteristic higher than A, while in the pre-commitment and GI subgame perfect equilibria improvements were defined with respect to threshold C.

Conclusion and extensions

The current paper has presented an equilibrium model of [rational] demand for technology and strategic supply that verifies formally the economic intuition developed by Malerba et al. (2003, 2007) and relates it to the results obtained by the operations research literature (Jensen, 1988; Cho & McCardle, 2009; Ulu & Smith, 2009). We have demonstrated how, after observing a positive credible signal, perfect foresight DMs are more willing to start searching for a product in the corresponding signaled market. However, perfect foresight triggers a slow-down in the adoption of the technology becoming available with respect to myopia. Even when considering consumption inertia and IDs, the realization of X_1 required by perfect foresight DMs from the unsignaled market is quite higher than the one required by myopic DMs.

Binary comparisons are common in most decision problems dealing with multiple criteria. In this regard, the formal structure introduced in the paper is sufficiently malleable to incorporate a third firm into the analysis. In this case, we should consider an additional set of potential realizations per characteristic – describing the products of the third competitor – and expand the expected utilities and transition matrices accordingly. The strategic framework would become substantially more complex while allowing for additional interactions among firms. Intuition regarding the effects derived from incorporating a third alternative to the analysis can be found in Di Caprio et al. (2016), together with the corresponding formal analyses.

The current analysis of technological demand complements the evolutionary branch of the literature that focuses on processes breaking out of an existing technological trajectory (Dolfsma & Leydesdorff, 2009; Roy, 2018; Kanger et al., 2019). The resulting policy implications range from the creation of programs to educate consumers on recent technological developments to the actual acquisition of technology by public institutions. For instance, it seems natural to assume that higher levels of experience and technical education are coupled with a higher tendency to experiment with novel products. In this regard, the capacity of DMs to observe and assimilate signals may also be determined by their experience as users and their level of technological education. Thus, the existence of relatively less educated, i.e., myopic, DMs exhibiting a higher degree of risk-aversion increases the probability of suboptimal locking-in events. As a result, myopic DMs should be considered when analyzing the pervasiveness of inferior products supplied by local monopolies within technologically underdeveloped countries and the inability of the latter to induce a sufficient pull in demand to trigger the introduction of further innovations.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jik.2022.100193.

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