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FORMALISING THE DEMAND FOR TECHNOLOGICAL INNOVATIONS: RATIONAL HERDS, MARKET FRICTIONS AND NETWORK EFFECTS

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The current paper presents a theoretical model where rational decision makers (DMs) observe credible signals regarding the existence of technologically superior products and

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generate the demand structure determining their evolution within the market. We will illustrate how consumers may stick to an inferior product when market frictions or their own expectations dictate them to do so. This will be the case even if the newcomer firm credibly guarantees an improvement upon the main characteristics of the incumbent product. Indeed, the prevalence of a suboptimal technology can be the result of the correct choice being made at a given point in time. Moreover, we will compute the expected prevalence of a given product in the market when information regarding the existence of a technologically superior product spreads across consumers following different diffusion processes. The consequences derived from the existence of path dependence phenomena will be analysed from a dynamic perspective by explicitly accounting for the emergence of network effects that may take place after firms signal the availability of a technologically superior set of products.

Keywords: Technology demand; technological evolution; credible signals; search frictions; network effects.

Introduction

Motivation

The importance of demand-based industrial dynamics is becoming increasingly evident in the recent evolutionary economics literature, see Klepper and Malerba (2010) and the papers within the corresponding special issue. In this sense, van den Ende and Dolfsma (2005) illustrate how the *emergence* of new technological paradigms may also be enabled by demand factors. These authors try to overcome the selective role among and *within* different paradigms generally assigned to demand, a view originally emphasised by Dosi (1988). However, the studies of demand evolution have been mainly developed from a macroeconomic diffusion perspective, ranging from the original Bayesian learning model of Stoneman (1981) to the most recent computable versions of Barbiroli and Ritelli (1997), Aversi *et al.* (1999), Fatas-Villafranca and Saura-Bacaicoa (2004) and Malerba *et al.* (2007).

The approach to the behaviour of demand followed in the current paper will be based on the idea of products being defined by two-dimensional (2D) vectors of characteristics. Such an approach is not only typical of the consumer choice literature (Bearden and Connolly, 2007), but has also been employed to measure technological evolution in the economics one (Saviotti, 1982; Alexander and Mitchell, 1984; Saviotti and Metcalfe, 1984). These authors based their empirical studies on sets of characteristics describing the technology implicit within different heterogeneous products and developed indicators to measure the effects of technological innovation and change (sophistication) on the characteristics and valuation of the products.

These ideas, based on the seminal analysis of Lancaster (1966), will be applied here to define the information acquisition and choice behaviour of consumers or

decision makers (DMs). In particular, we will focus on two categories of characteristics determining the transition between different products and markets. Despite the apparent formal simplicity of the model, the information gathering and decision processes of DMs, based on the existence of endogenously generated quality thresholds, are far from trivial and will allow for the design of a demand structure able to account for signals, learning, search and matching frictions as well as network and diffusion effects. In addition, our decision theoretical structure is based on relatively straightforward technical assumptions leading to clear choice and demand patterns among DMs.

We are aware of and recognise the limitations faced when operating within a purely decision theoretical environment as well as the lack of empirical validity exhibited by the axioms of expected utility (Di Caprio and Santos Arteaga, 2011). Despite this fact, we will model the behaviour of DMs using both these axioms and the corresponding implicit economic intuition. At the same time, considering the simplest possible information gathering and choice environment will allow us to accommodate the main behavioural assumptions highlighted by the endogenous preference approach of Aversi *et al.* (1999). In particular, information gathering costs will be omitted, though they can be trivially introduced, and we will define a lexicographic-like choice structure on a set of products that are composed by two categories of characteristics. It could be assumed that personal and social environmental features are either implicit to the information gathering structure or could be included when defining the characteristics considered as the most important ones by DMs (Aversi *et al.*, 1999).

We will not provide DMs with the sophistication required so as to become users in the sense of von Hippel (1988) and Rogers (2003), i.e., able to interact with the supplier in order to improve the product, even though their choices do indeed determine the survival of some products and technologies and not others. For example, Brown and Greenstein (2000) identified econometrically the lead users that helped creating niche markets for new technological products within the computer industry using data on the demand for speed and memory (two main characteristics) of mainframe computers during the second half of the eighties.

Following Geroski (2000), we will concentrate our efforts in analysing the technological transition behaviour of DMs at the most basic microeconomic level. At the same time, we will illustrate how this basic setting can be easily extended to analyse the behaviour of DMs when considering the potential information diffusion trends associated to the innovation process. Indeed, according to the dominant design concept of Utterback and Abernathy (1975), see also Utterback (1996), new technologies are introduced in the market in a variety of forms, often leading to a small explosion in new products, or new product variants, until a dominant design emerges and evolves.

Description

The paper will be divided in three different formal settings, each analysed both theoretically and numerically. These settings extend the analysis introduced in Di Caprio and Santos Arteaga (2014). In that paper, the authors concentrate on the game theoretical effects derived from different information acquisition structures. These effects determined the different Nash equilibria obtained based on the information acquisition process selected by the DMs. In the current setting, we concentrate on the transition processes triggered by the introduction of technologically superior innovations. These processes are demand-based and determined by the information acquisition behaviour of the DMs, which allows the current analysis to complement the findings obtained by Di Caprio and Santos Arteaga (2014).

The first setting focuses on the concept of performance thresholds described by Adner and Levinthal (2001) and illustrated by Di Caprio and Santos Arteaga (2014). The natural emergence of decision thresholds within our theoretical environment will be used to illustrate how the risk attitudes of consumers affect the assimilation of disruptive technologies. In the current setting, these technologies have already been developed by the firm but must be introduced in the market (Adner, 2002). Indeed, a superior distribution of desirable variants of the product characteristics will be generated, as is required for the development of a new market (Abernathy and Utterback, 1978). However, we will show how DMs become more reluctant to consider the purchase of the superior technology while requiring an improvement in the realisations of the characteristics observed.

The intuition giving place to the second setting follows from Christensen and Rosenbloon (1995) and relates directly to their analysis of nested hierarchies and value networks: "The viewpoint that differences in firms" market positions drive differences in how they assess the economics of alternative technological investments is rooted in the notion that products are systems comprised of components which relate to each other in a designed architecture [. . .] Furthermore, the end-product may also be viewed as a component within a system-of-use, relating to other components within an architecture defined by the user. In other words, products which at one level can be viewed as complex architected systems act as components in systems at a higher level." (Christensen and Rosenbloon, 1995, p. 238).

In particular, when evaluating the product attributes considered to be central for the network, the list of characteristics reduces to two or three per product (Christensen and Rosenbloon, 1995, p. 239). Specifically, Christensen and Rosenbloon (1995, p. 240) state that associated with each network is a unique rank-ordering of the importance of various performance attributes, whose

rank-ordering differs from that employed in other value networks. In this sense, our DMs will subjectively account for the expected relative performance of their most preferred attributes when determining their information gathering and demand incentives. It is within this setting that we will develop our analysis of lock-in effects and path dependence described in the next subsection.

Our final decision theoretical setting relates to the classical representation of technological competition described by Foster (1986) and restated by Adner and Snow (2010), which focuses on the ability of old technology incumbents to recognise plausible threats and manage the adoption of the new technology on time. Antonelli (1993) illustrates the pervasive effects derived from being locked-in into a large base of the (old) inferior technology so that high costs from switching to the (new) superior one are faced. We will therefore be considering our decision theoretical structure from a dynamic managerial perspective, since, after all, it is firm's managers who must decide whether or not to introduce a technologically superior product in the market given its expected rate of diffusion and acceptance. We will also indirectly account for the remarks made by Geroski (2000) when referring to the creation of a new market and the fuzziness involved in the demand of DMs for the corresponding innovation due to their little practical knowledge or experience of the innovation itself.

Main contribution: on lock-in effects and path dependence

Lock-in and path-dependent phenomena constitute an important topic of research among evolutionary economists, who are determined to provide empirical cases illustrating these phenomena that go beyond the seminal QWERTY and Beta versus VHS discussions on which the literature focused initially (Antonelli, 2003; Hanusch and Pyka, 2007). The concept of path dependence and, in particular, the lock-in process defining the generation of paths, have gained substantial relevance in the business literature (Sydow *et al.*, 2012). Their applications range from the effect that environmental complexity has on sequential decision-making processes (Koch *et al.*, 2009) to the strategic role of path dependence within the organisation (Koch, 2011), and have even extended to the economic geography literature (Martin and Sunley, 2006).

Given the difficulties involved in the detection of choices that were suboptimal when a decision was made, an identification problem arises when relating the properties of empirical complex systems to the economic environment (Durlauf, 2005). As a result, the initial dispute between the main supporters of the path dependence phenomenon (David, 1985, 1988, 1992) and its detractors (Liebowitz and Margolis, 1990; Lewin, 2002) continues nowadays (Liebowitz and Margolis, 2013).

An important lacuna in both these lines of research is the *ad hoc* assumptions made on the behaviour of consumers without defining an actual decision model of information acquisition and choice that determines their corresponding product switch incentives. That is, the incentives determining the acceptance of a technology within an incomplete information setting remain undefined from the point of view of the DM. We are not going to enter into the discussion maintained by both research lines throughout the latter years regarding the empirical validation of lock-in and path dependence phenomena.

However, we will concentrate on the assumption made by the detractors of the path dependence phenomenon regarding the fact that suboptimal technological choices give place to outcomes that should be immediately recognised as such and modified. We will illustrate that this is not necessarily the case and that consumers are able to prevent this type of situations and define virtuous technology cycles while also allowing for inferior technologies to prevail due to market frictions or their expectations about the evolution of a given alternative. The model introduced in this paper illustrates the existence of both possibilities and how consumers may actually stick to an inferior product when market frictions or their own expectations dictate them to do so. Indeed, the prevalence of a suboptimal technology can be the result of the correct choice being made at a given point in time.

In order to describe the main implications of our decision model, we will revisit the Netscape versus Internet Explorer case study analysed by (Liebowitz and Margolis, 2001) and illustrate how, despite being considered initially superior to the Internet Explorer alternative and recognised as such by the consumers, the Netscape browser could still be displaced from the market by the former.

In this regard, our decision model implies that different technologies can compete and coexist within a given market depending on the characteristics of the consumers and their expectations. The strategic consequences derived from this type of scenario have been described by Tavana *et al.* (In Press). Similarly, Onufrey and Bergek (2015) have illustrated how different technologies can coexist within a market while defining multiple technological paths in the presence of positive reinforcement mechanisms.

The rest of the paper is organised as follows. Sections 2 and 3 define the optimal information gathering behaviour of DMs. The three formal settings described above are introduced in Secs. 4–6, respectively. In particular, Sec. 4 adds signals and learning to the basic model. Section 5 focuses on the effect that search and matching frictions have on the information acquisition incentives and the resulting demand of DMs. Section 6 accounts for potential technology diffusion and network effects from the supplier's point of view. Finally, Sec. 7 summarises the main findings and suggests possible extensions.

Notations and Working Hypotheses

If extended, the basic information acquisition structure described through the paper would require DMs to consider all possible outcomes resulting from any current decision before making it. This implies that the information acquisition incentives of DMs should be redefined in terms of *all the previously observed realisations*, *their sets of potential combinations and the corresponding expected payoffs*, preventing the use of standard dynamic programming techniques.

As a result, the current information acquisition structure limits the capacity of DMs to account for decision problems consisting of large numbers of observations (Di Caprio *et al.*, 2016). The imposition of this type of structure within the current paper is justified by the low dimensionality of the model and the memory capacity with which DMs are endowed when comparing products in basic information evaluation scenarios. Even though such an assumption becomes prohibitive in larger dimensional settings, it is imposed here to account for the satisficing capacity constraints defined by Simon (1997) within a fully rational environment.

At the same time, it should be noted that products are composed by multiple characteristics that can be defined as part of different categories. Following the bounded rationality approach introduced by Simon (1997), the characteristic factor spaces described below can be interpreted as categories and the thresholds derived from the search functions as satisficing constraints. This interpretation simplifies the dimensionality problem and adds dynamic intuition to the model, particularly when considering the results presented in Sec. 6.

The notations and initial assumptions used in this paper follow Di Caprio and Santos Arteaga (2009, 2014) and Di Caprio *et al.* (2014). We restate most of them in order to keep the current paper self-contained. Denote by G the set of all products. Our basic working hypothesis is the following:

(I) G consists of at least two products and the DM is allowed to collect two pieces of information, not necessarily from the same product.

As a consequence, we can assume all products to be described by two characteristics, that is, every product in G to be identified with a pair (x_1, x_2) belonging to the Cartesian product $X = X_1 \times X_2$, where each X_i, $i = 1, 2$, is the set of all the "values" that can be assigned to the ith characteristic of the product. Each X_i will be called the *ith characteristic factor space*, while X will be referred to as the *characteristic space*.

Moreover, we assume the following.

(II) For $i = 1, 2$, $X_i = [x_i^m, x_i^M]$ where x_i^m, $x_i^M > 0$, with $x_i^m \neq x_i^M$.

(III) The DM orders the characteristic space X by a strict preference relation denoted by $\succ$.

(IV) The preference relation $\succ$ is representable by a continuous additive utility function: $\exists u : X \to \Re$, $u_1 : X_1 \to \Re$, $u_2 : X_2 \to \Re$ continuous s.t. $u(x_1, x_2) = u_1(x_1) + u_2(x_2)$

(V) For $i = 1, 2$, $\mu_i : X_i \to [0, 1]$ is a continuous probability density on X_i with support $\mathrm{Supp}(\mu_i) = \{x_i \in X_i : \mu_i(x_i) \neq 0\}$.

The symbol $>$ denotes the standard strict order on the reals.

Remark. The results introduced through the paper are derived for continuous probability densities. The remaining cases, quite similar to the continuous one, are left to the reader. The probability densities are also assumed to be independent, but our information acquisition structure allows for subjective correlations between the two characteristic of a given product. Finally, following the standard economic theory of choice under uncertainty, we assume that:

(VI) for $i = 1, 2$, the DM elicits the *certainty equivalent value induced by* μ_i *and* u_i, denoted by ce_i, as the reference point against which to compare the information collected on the ith characteristic of any product. That is, the DM is indifferent between the value ce_i in X_i and the one he can expect to obtained through μ_i and u_i.

For $i = 1, 2$, we have $\mathrm{ce}_i = u_i^{-1}(E_i)$, where $E_i = \int_{X_i} \mu_i(x_i) u_i(x_i)\, dx_i$ is the expected value of u_i.

The existence and uniqueness of the certainty equivalent value ce_i in X_i are guaranteed by the continuity and strict increasing of u_i, respectively.

Basic Criterion to Optimally Acquire Information

As assumed above, we consider the case of a DM who is allowed to collect two pieces of information. This implies that the DM can collect information about a maximum of two products. Henceforth, we denote by J and K the first and second products that can be randomly checked by the DM. The DM can check either the values of both characteristics of J or the values of the first characteristic of both J and K. While the first information to acquire must be necessarily the value of the first characteristic of J, the DM can use the second piece of information to check either the value of the second characteristic of J or the value of the first characteristic of K. In other words, the DM can decide to either continue acquiring information on the initial product J or starting with a new product K.

In Di Caprio and Santos Arteaga (2009, 2014), the authors introduce two real-valued functions $F : X_1 \to \Re$ and $H : X_1 \to \Re$, that allow the DM to evaluate his

expected utility gain over the sum $E_1 + E_2$ both in the case when he decides to continue checking product J and when he decides to start checking product K. Consequently, if x_1 is the value observed for the first characteristic of J, how the DM decides to allocate the second piece of information depends on which is the highest value between $F(x_1)$ and $H(x_1)$.

The functions F and H are defined as follows.

For every $x_1 \in X_1$,

$$F(x_1) \stackrel{\text{def}}{=} \int_{P^+(x_1)} \mu_2(x_2)(u_1(x_1) + u_2(x_2))dx_2 + \int_{P^-(x_1)} \mu_2(x_2)(E_1 + E_2)dx_2 \tag{1}$$

with

$$\begin{aligned} P^+(x_1) &= \{x_2 \in X_2 : u_2(x_2) > E_1 + E_2 - u_1(x_1)\} \\ P^-(x_1) &= \{x_2 \in X_2 : u_2(x_2) \leq E_1 + E_2 - u_1(x_1)\} \end{aligned}, \tag{2}$$

and

$$\begin{aligned} H(x_1) \stackrel{\text{def}}{=} & \int_{Q^+(x_1)} \mu_1(y_1)(u_1(y_1) + E_2)dy_1 \\ & + \int_{Q^-(x_1)} \mu_1(y_1)(\max\{u_1(x_1), E_1\} + E_2)dy_1, \end{aligned} \tag{3}$$

where

$$\begin{aligned} Q^+(x_1) &= \{y_1 \in X_1 : u_1(y_1) > \max\{u_1(x_1), E_1\}\} \\ Q^-(x_1) &= \{y_1 \in X_1 : u_1(y_1) \leq \max\{u_1(x_1), E_1\}\} \end{aligned}, \tag{4}$$

$P^+(x_1)$ and $P^-(x_1)$ define the intervals of all values for the second characteristic x_2 of product J such that the utility of product J, $u_1(x_1) + u_2(x_2)$, is respectively higher than or lower-equal to the expected utility of a product randomly chosen from G, $u_1(\text{ce}_1) + u_2(\text{ce}_2) = E_1 + E_2$.

In the case when $u_1(x_1) + u_2(x_2) \leq E_1 + E_2$, then choosing a product from G randomly delivers an expected utility higher than the expected utility obtained from choosing product J. Hence, if x_2 of product J is in $P^-(x_1)$, the DM will prefer to choose a product randomly.

Similarly, $Q^+(x_1)$ and $Q^-(x_1)$ define the intervals of all values for the first characteristic y_1 of product K such that the expected utility of product K, $u_1(y_1) + u_2(\text{ce}_2)$, is respectively higher than or lower-equal to the maximum between the expected utility of product J, $u_1(x_1) + u_2(\text{ce}_2)$, and that of a product randomly chosen from $G, u_1(\text{ce}_1) + u_2(\text{ce}_2) = E_1 + E_2$.

In particular, if y_1 of product K is in $Q^-(x_1)$, that is, $u_1(y_1) \leq \max\{u_1(x_1), E_1\}$, then the DM will choose either J and or a random product, but not K.

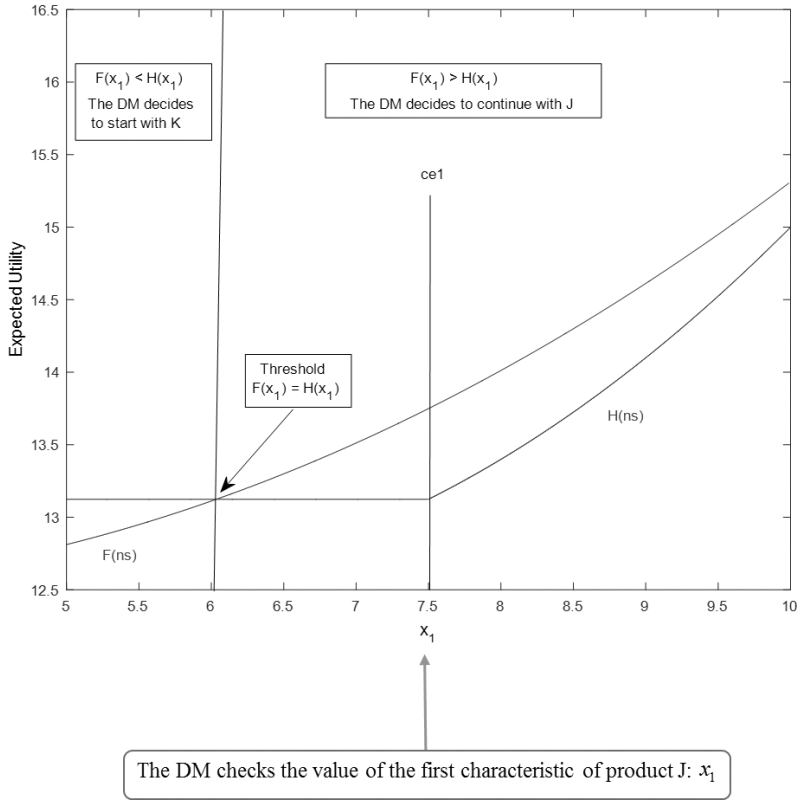


Fig. 1. Basic criterion to optimally acquire information.

The criterion used by the DM to decide how to *optimally* use the second piece of information, once he has checked the value of the first characteristic of product J and obtained the value x_1 is outlined in Fig. 1. If $F(x_1) = H(x_1)$, the value x_1 can be interpreted as a "threshold" delimiting the transition between products.

Signals and Learning

In this section, we analyse the effect that positive signals indicating the existence of a technological innovation have on the information acquisition behaviour of the DMs. Signals are introduced on the probability distribution of X_2 in order to separate the effect of the actual X_1 observations from the role played by expectations. We will assume without loss of generality that uniform probability densities are defined on both X_1 and X_2.

Remark. Even though we will concentrate on the effect that the first-order stochastic dominance resulting from the signal has for the uniform density case, our analysis can be generalized to any other density function whose probability mass is redistributed to generate higher expected utilities, see Chapter 6 in Mas-Colell *et al.* (1995).

Thus, we assume that:

(VII) There exists $\alpha, \beta \geq 0$, with $\alpha < \beta$, such that:

$$\mu_2(x_2) = \begin{cases} \dfrac{1}{\beta - \alpha} & \text{if } x_2 \in [\alpha, \beta] \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

We also assume that

(VIII) Receiving a credible positive signal, θ, regarding the probability μ_2 on X_2 implies that a percentage γ of the probability mass accumulated on the lower half of the distribution is shifted to the upper half. The corresponding conditional density function is given by

$$\pi(\theta|x_2) = \begin{cases} \dfrac{1+\gamma}{\beta - \alpha}, & \text{if } x_2 \in \left(\dfrac{\alpha+\beta}{2}, \beta\right], \\ \dfrac{1-\gamma}{\beta - \alpha}, & \text{if } x_2 \in \left[\alpha, \dfrac{\alpha+\beta}{2}\right]. \end{cases} \tag{6}$$

After receiving a positive signal, a rational DM updates his initial beliefs, given by $\mu_2(x_2)$, following Bayes' rule. Therefore, if a signal is received, i.e., $\theta = 1$, the updated beliefs of the DM will be given by

$$\mu_2(x_2|\theta = 1) = \frac{\pi(\theta|x_2)\mu_2(x_2)}{\int_{X_2} \pi(\theta|x_2)\mu_2(x_2)dx_2}. \tag{7}$$

The updating process proceeds in the same way as the DM receives additional signals. The corresponding (Bayesian) updated functions $F(x_1|\theta = 1)$ and $H(x_1|\theta = 1)$ defining the information gathering process of the DM through the signalled market are given by

$$\begin{aligned} F(x_1|\theta = 1) &\stackrel{\text{def}}{=} \int_{P^+(x_1|\theta=1)} \mu_2(x_2|\theta = 1)(u_1(x_1) + u_2(x_2))dx_2 \\ &+ \int_{P^-(x_1|\theta=1)} \mu_2(x_2|\theta = 1)(E_1 + E_{(2|\theta=1)})dx_2 \end{aligned} \tag{8}$$

with

$$\begin{aligned} P^{+}(x_1|\theta=1) &= \{x_2 \in X_2 : u_2(x_2) > E_1 + E_{(2|\theta=1)} - u_1(x_1)\} \\ P^{-}(x_1|\theta=1) &= \{x_2 \in X_2 : u_2(x_2) \leq E_1 + E_{(2|\theta=1)} - u_1(x_1)\} \end{aligned}, \tag{9}$$

and

$$\begin{aligned} H(x_1|\theta=1) \stackrel{\text{def}}{=} & \int_{Q^{+}(x_1)} \mu_1(y_1)(u_1(y_1) + E_{(2|\theta=1)})dy_1 \\ & + \int_{Q^{-}(x_1)} \mu_1(y_1)(\max\{u_1(x_1), E_1\} + E_{(2|\theta=1)})dy_1, \end{aligned} \tag{10}$$

where

$$E_{(2|\theta=1)} = \int_{X_2} \mu_2(x_2|\theta=1)u_2(x_2)dx_2. \tag{11}$$

It can be easily shown analytically that if $\mu_2(x_2|\theta=1)$ first-order stochastically dominates $\mu_2(x_2)$, then both $F(x_1|\theta=1) \geq F(x_1)$ and $H(x_1|\theta=1) \geq H(x_1)$. See Di Caprio *et al.* (2014) for a complete proof of this result.

DMs shift from the unsignalled market to the signalled one in order to try to improve (in expected utility terms) upon the set of products offered within the former market through their information gathering processes. In this regard, Malerba *et al.* (2003, p. 8) refer to sophisticated customers as those customers who "won't buy a new model computer unless it is as good as or better than the old model ones". Eng and Quaia (2009) provide a review of the literature emphasising the essential role played by continuous customer learning and education in the communication process of firms. This is particularly the case when firms need to communicate the benefits derived from a technological innovation to customers and reduce their perceived risks and uncertainties regarding the new product.

As a result, two main types of information gathering scenarios will be considered when defining the incentives of DMs to shift between products. Each scenario leads to its own set of threshold values based on the expected improvements that may be guaranteed by the signalling firms when DMs shift between products. We start by considering the simplest possible scenario, where basic information gathering herds arise absent search frictions and consumption inertia.

Numerical simulations: credible signals, information gathering herds and stricter continuation criteria

The numerical sections of the paper will present several simulations that illustrate the behaviour of the optimal threshold values as the DMs receive *credible* signals

indicating the existence of a technologically superior set of products while being subject to the information gathering constraints imposed within each corresponding subsection. Throughout the simulations, the DMs will be assumed to have a well-defined preference order both *within* and *between* characteristics. That is, the first characteristic will be assumed to be more important for DMs and, therefore, lead to a higher expected utility than the second one (Bearden and Connolly, 2007; Di Caprio and Santos Arteaga, 2014). In order to facilitate comparisons among the threshold values generated by different numbers of signals and types of DMs, the support of all the probability functions will be kept unchanged through the simulations.

Throughout the simulations, the risk-neutral reference case will be described by the following parameter values

- characteristic spaces: $X_1 = [5, 10]$, $X_2 = [0, 10]$;
- utility functions: $u_1(x_1) = x_1$, $u_2(x_2) = x_2$;
- probability densities, both continuous and uniform: $\forall x_1 \in X_1,\ \mu_1(x_1) = \frac{1}{5}$; $\forall x_2 \in X_2,\ \mu_2(x_2) = \frac{1}{10}$;
- percentage of probability mass shifted: $\gamma = \frac{1}{2}$.

The risk-averse reference case has the same characteristic spaces and probability densities as the risk-neutral one, but its utility functions are given by $u_1(x_1) = \sqrt{x_1}$ and $u_2(x_2) = \sqrt{x_2}$. It should be highlighted that modifying the functional values or the support of the densities does not affect the main results obtained.

In all 2D figure the horizontal axis represents the set of x_1 realisations that may be observed by the DM, with the corresponding subjective expected utility values defined on the vertical axis and the certainty equivalents explicitly identified through a vertical line.

Figure 2 illustrates the one and two signals cases, denoted by $1s$ and $2s$, respectively, and the evolution of the corresponding threshold values within a basic risk-neutral scenario. Points A, B and C identify the threshold values defined by DMs when gathering information on a set of products located within the unsignalled, one signal and two signals markets, respectively.

Figure 3 illustrates the same environment as Fig. 2 but within a risk-averse setting, where the utilities with which DMs are endowed have been shifted from basic linear functions to square roots.

Clearly, positive signals generating first-order stochastic dominant beliefs lead to higher expected utility levels for all possible values of x_1. However, in doing so, signals shift the respective optimal threshold values towards higher x_1 realisations.

The intuition arising from these results implies that positive signals should generate immediate herds of consumers towards the subset of products on which

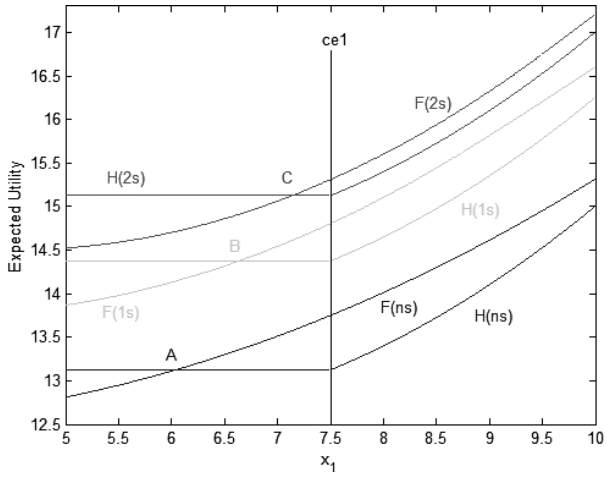


Fig. 2. Evolution of optimal threshold values given risk-neutral utility functions and uniform risk distributions.

they are defined, but, at the same time, DMs, who expect a higher value of E_2 to be guaranteed from their information gathering process, become less search averse within the corresponding subset, i.e., the area where the function H remains above the function F increases for relatively low x_1 realisations. As a result, DMs would require relatively higher realisations from the first characteristic space in order to continue gathering information on the product observed. That is, DMs would reject partially observed products with a higher probability than in the unsignalled market.

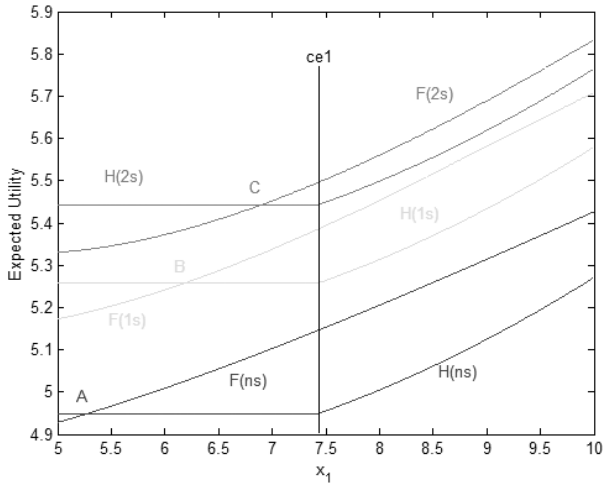


Fig. 3. Evolution of optimal threshold values given risk-averse utility functions and uniform risk distributions.

Such an effect can also be observed in the risk-averse setting illustrated in Fig. 3. Note, however, the increase in search aversion relative to the linear risk-neutral case, an effect already described by Di Caprio and Santos Arteaga (2009). Thus, as risk-aversion increases, an increase in the information gathering continuation area follows. Other than that, the signal effects are identical to those observed in the risk-neutral case.

The main implicit assumptions defining the current setting, i.e., signal credibility, and the absence of both search frictions and consumption inertia, have been imposed to reflect the frictionless environment required for DMs to generate an information gathering herd after becoming aware of the existence of a set of technologically superior products. We have just seen that, even in this case, the resulting herd does not necessarily lead to faster adoption within the set of signalled products. At the same time, the presence of search frictions and basic consumption inertia implies that the information gathering transition between markets is not necessarily guaranteed, even if signal credibility is maintained. The following section illustrates this type of theoretical setting.

Search and Matching Frictions

The previous subsection has analysed numerically the effects that positive signals and changes in the risk attitude of the DM have on his optimal information gathering behaviour. The resulting search aversion derived from increments in the risk-aversion coefficient of DMs was obtained absent search frictions of any type. However, the existence of search and matching frictions is known to condition the optimal search behaviour and the demand of DMs. Even though the effect that frictions may have on the behaviour of $H(x_1)$ is intuitively clear, this section provides the theoretical basis for its posterior simulation.

Consider a DM who has just checked the first characteristic of a given product, x_1, and must decide whether to check the second characteristic from the same product or start acquiring information on a new product from the signalled market. It will be assumed that the probability that retrieving the next observation from a new product pays off, meaning that at least l within m available products satisfy the *inherent* search parameters fixed by the DM, is given by the following cumulative binomial distribution

$$\psi(m, l, f) = \sum_{j=l}^{m} \binom{m}{j} f^j (1-f)^{m-j}, \tag{12}$$

where f represents the probability assigned by the DM to the fact that a product satisfies his subjectively defined requirements. That is, given the large variety of

products available to observe and purchase, the DM must add to his search process a matching probability accounting for his expectation of what percentage from the newly introduced products will indeed satisfy his future network requirements. In this regard, f could be interpreted as the subjective probability associated by the DM to any of the new products achieving the status of or becoming as widespread [diffused] as the currently available ones.

Given this probability, the DM requires a minimum percentage of the newly introduced products expected to develop (achieve) a sufficiently large network (diffusion) to become available during the search process. These effects are particularly important when considering the evolution and diffusion of increasingly complex technological products. A recent example would be given by the set of available e-books and the respective formats they are compatible (and incompatible) with.

An alternative interpretation of the binomial parameters would consist of defining f as the probability that a consumer shifts his information acquisition process and adopts the new product while requiring at least l out of m consumers to adopt the new products during the search process. We will follow this interpretation in the subsequent sections.

Even though the search process allows the DM to observe several characteristics from a product, other inherent characteristics remain directly unobservable and will either become apparent after purchasing the product or must be subjectively forecasted by the DM. The former problem was identified by Nelson in 1970. He stated that while prices are directly observable, other characteristics defining the overall quality of products require consumption. Search processes must therefore be defined by price and experience components, the latter requiring the actual consumption of the product to be observed (Nelson, 1970). The latter problem relates to the existence of network, lock-in and bandwagon effects in the consumption process of products, see Geroski (2000) for a review of the literature. That is, while current products have an established network of connections and are largely compatible with other existing products, newly introduced products may fail to develop such a quality.

Note that $\psi(m, l, f)$ combines the standard textbook approach to technology spreads and learning from Aghion and Howitt (1998), given by the cumulative binomial form of the function, and a matching process commonly used in the economic search literature, see McCall and McCall (2008). In this way, the subjective diffusion expectations implicitly defined within f are separated from the minimum friction requirements imposed on the search process via l and m. Thus, the probability of finding a product that matches the inherent characteristics required by the DM is given by $\psi(m, l, f)$. The expected payoff obtained from remaining checking of the first product is $F(x_1)$, while that from starting gathering information on a second signalled product must consider the search and matching

frictions defined above and is therefore given by $\psi(m, l, f)H(x_1|\cdot)$. As a result, the transition between unsignalled and signalled markets will be based on the following comparison

$$\begin{aligned} &\text{either } F(x_1) > \psi(m, l, f)H(x_1|\cdot) \\ &\text{or } F(x_1) < \psi(m, l, f)\, H(x_1|\cdot). \end{aligned} \tag{13}$$

The numerical simulations introduced through the following subsections will combine changes in both search and matching frictions to illustrate the main transition results obtained. Clearly, the interpretation of the results differs depending on the friction effect that one wants to emphasise. We will refrain from doing so and concentrate on the general effect that market frictions have on the information gathering behaviour and the demand of DMs.

Numerical simulations: multiple thresholds and decision reversibility

The current search and matching frictions setting has been explicitly designed to capture the effects that habits and consumption inertia have on the information gathering process of DMs. That is, the existence of search and matching frictions provides a natural framework for DMs to also exhibit inertia, a condition much harder to justify intuitively within the previous (pure) herding environment, where the function $H(1s)$ remains above $F(ns)$ for all $\forall x_1 \in X_1$. In this sense, observing a signal whose intensity or strength is weakened by the existing frictions, such that the resulting function $H(1s)$ crosses $F(ns)$ at some $x_1 \in X_1$, allows for a straightforward justification of the inertia assumption.

In the current setting, consumption inertia implies that despite the recognised technological superiority of the set of signalled products, DMs may be initially reluctant to shift their information gathering processes to the signalled market and, therefore, they gather their first observation from the unsignalled one. As already stated, the existence of network effects could also provide the required intuition, since it is always challenging for DMs to be among the first consumers of a new technology while abandoning an already established one. The next theoretical setting will analyse this scenario in more detail. Note, however, that the computational sophistication required from DMs to account for the dynamic evolution of different sets of products will make the analysis more plausible if it is considered from the supply side.

We allow for habits and consumption inertia in order to account for the fact that the existence of a technologically superior set of products does not necessarily imply an immediate transition to the market generated by the newly introduced technology (Geroski, 2000; Heidenreich and Spieth, 2013). Moreover, as emphasised by Malerba *et al.* (2003), the introduction of a new product within a

given industry relies on the existence of experimental consumers, who may allow for its survival through the creation of specialized niche markets. In this sense, the degree of experimentation exhibited by a consumer could be assumed to be implicitly defined within or approximated by $\psi(m, l, f)$.

In order to provide an intuitive description of the results obtained, we will define the products whose first characteristic is located in the vicinity of the certainty equivalent value as mediocre. At the same time, products become relatively optimal as their initial characteristic gets closer to x_1^M. Similarly, products become relatively suboptimal as their initial characteristic approaches x_1^m.

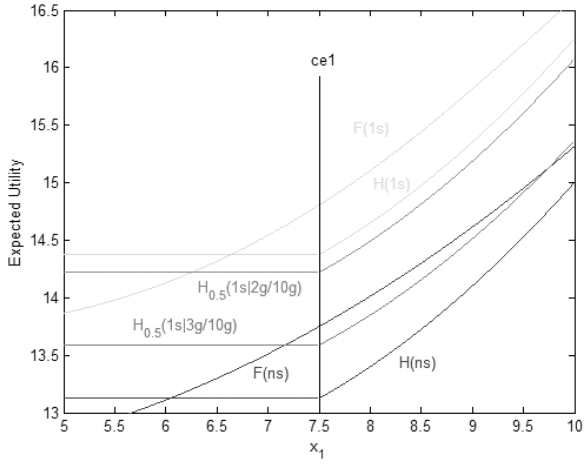
The following results summarize our main numerical findings regarding the effects that search and matching frictions may have on the information gathering and demand behaviour of DMs.

Lemma 5.1. *If the information gathering process of DMs is subject to search and matching frictions, then the transition between markets may not occur even if the DMs are willing to shift to the signalled market when the initial product observed is either relatively suboptimal or relatively optimal. Moreover, this is the case even if the signalling firm guarantees the first characteristic of its product to be at least as good as the x_1 observed within the unsignalled market.*

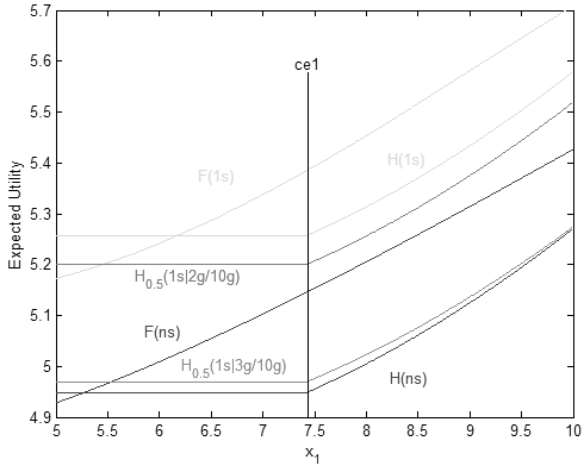
Lemma 5.2. *If multiple transition equilibria exist, the signalling firm may be forced to guarantee relatively high values of x_1 to trigger the transition between markets. In this case, the DMs will exhibit a reversal in their information acquisition incentives for relatively high values of x_1.*

The results described in these lemmas follow from Figs. 4 and 5, where different friction intensities have been simulated for a given identical signal. For instance, $H_{0.5}(1s|2g/10g)$ in Fig. 4(a) represents the original $H(1s)$ function weighted down by a binomial distribution $\psi(m, l, f)$ with the following coefficients: $m = 10$, $l = 2$ and $f = 0.5$. That is, the binomial coefficient f has been shifted from 1 to 0.5. At the same time, the DM requires at least two out of ten consumers to adopt the new products during the search process, i.e., $2g/10g$. The remaining functions in Figs. 4 and 5 have a similar interpretation.

Figures 4(a) and 4(b) illustrate how identical search frictions may generate multiple transition equilibria within the risk-neutral case but not within the risk-averse one. This type of result follows from the stricter continuation criteria that risk-neutrality gives place to relative to risk-aversion, an effect that we defined as search aversion in the previous section. Also, different values of f and l may give place to almost identical thresholds. For example, the function $H_{0.6}(1s|4g/10g)$, in Fig. 5(a), almost completely overlaps with $H_{0.5}(1s|3g/10g)$, in Fig. 4(a). As Figs. 5(a) and 5(b) illustrate, multiple transition equilibria can be generated



(a) Risk-neutral utility functions



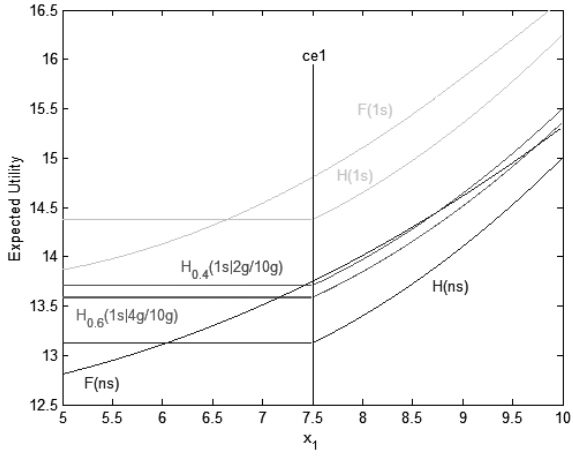
(b) Risk-averse utility functions

Fig. 4. Search and matching frictions: transition incentives.

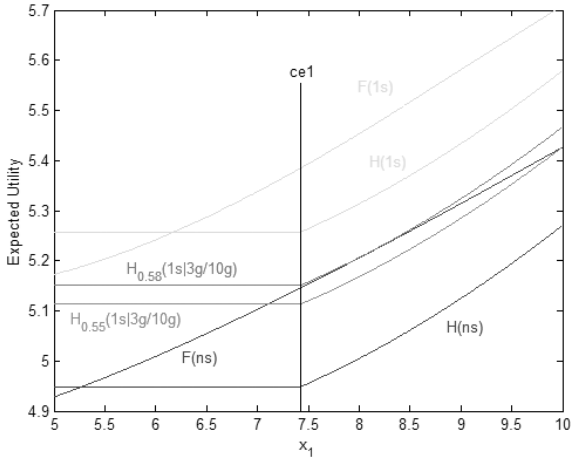
through different combinations of f and l in both information acquisition settings. The threshold values corresponding to Figs. 4 and 5 are provided in Tables 1 and 2 for the risk-neutral and risk-averse case, respectively.

Implications: search frictions and consumption inertia

The simulations presented in Figs. 4 and 5 illustrate how if, for example, brand education helps reducing (or creating) search frictions (Eng and Quaia, 2009), then incumbent firms may have a considerable advantage over newcomers when the



(a) Risk-neutral utility functions



(b) Risk-averse utility functions

Fig. 5. Varying search and matching frictions: transition incentives.

latter try to introduce a technologically superior product in the market. This is the case even though the definition of $H(x_1|\theta = 1)$ implies that the DM acknowledges the fact that the signalling firm will provide him with a product whose first characteristic is at least as high as the one observed in the unsignalled market, i.e., $y_{(1|\theta=1)} \geq x_1$.

Similarly, frictions affecting the strength or intensity of the signal could be assumed to be a function of the reputation of the firm signalling, which would provide well reputed incumbents with a considerable advantage over relatively unknown newcomers. Indeed, as the simulations show, the transition probability to

Table 1. Threshold values with risk-neutrality.

Function H	Threshold value
$H_{0.4}(1s\|2g/10g)$	7.4182 and 8.7345
$H_{0.5}(1s\|2g/10g)$	$H > F$; no threshold
$H_{0.5}(1s\|3g/10g)$	7.1662 and 9.7350
$H_{0.6}(1s\|4g/10g)$	7.1632 and 9.7443

Table 2. Threshold values with risk-aversion.

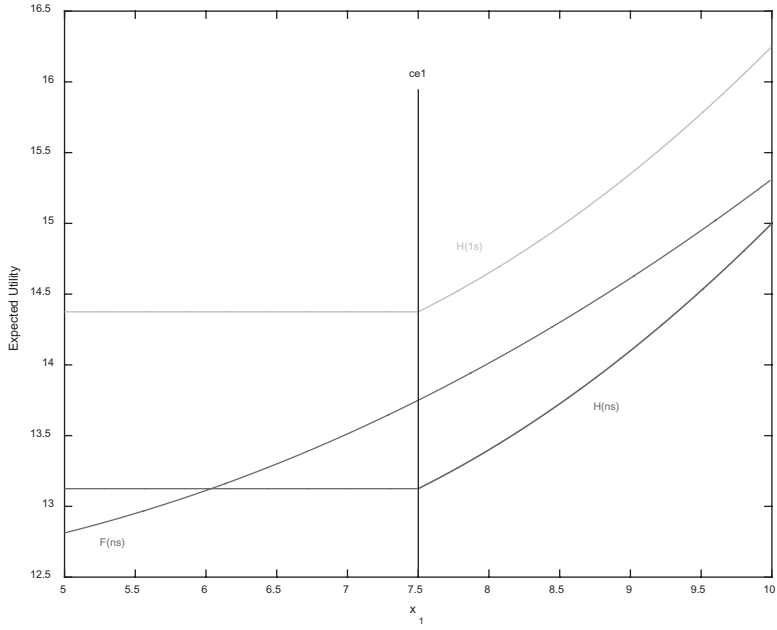
Function H	Threshold value
$H_{0.4}(1s\|2g/10g)$	$H > F$; no threshold
$H_{0.5}(1s\|2g/10g)$	5.5350
$H_{0.55}(1s\|3g/10g)$	7.1051 and 9.9955
$H_{0.58}(1s\|3g/10g)$	$H > F$; no threshold

the signalled market should be a *non-increasing* function of these frictions. Note that by transition probability, we are referring to the cumulative probability of the interval of $x_1 \in X_1$ realizations for which $H(x_1|\theta = 1) > F(x_1)$.

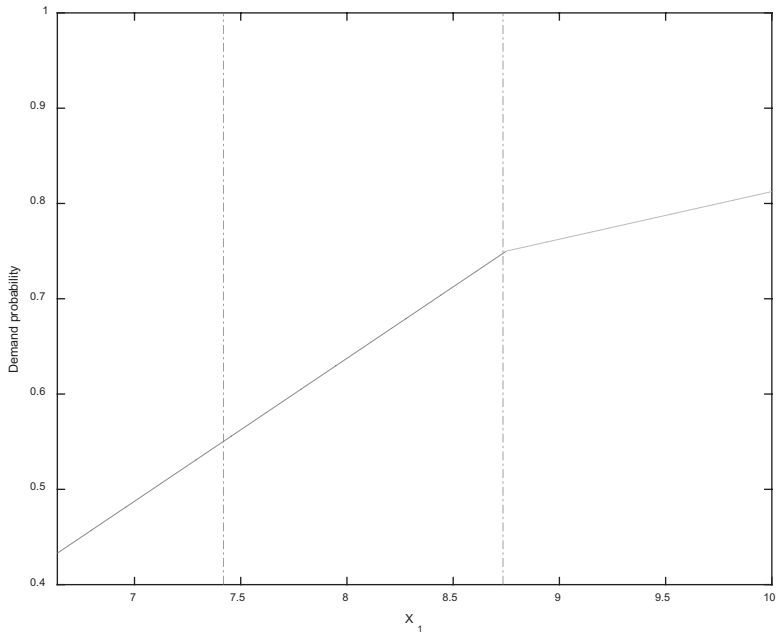
In this regard, Fontana and Guerzoni (2008) illustrate empirically how if interacting with customers helps reducing uncertainty, then firms with a high propensity to interact are more innovative and tend to introduce product innovations. These findings help emphasising the importance of consumer education in reducing search and matching frictions among DMs. In a related environment, Corrocher and Zirulia (2010) consider innovations in mobile communication services and show how demand provides both incentives to innovate and information about the behaviour of users when innovating within an uncertain context. In particular, they find that the customer base plays an important role in shaping firm's strategies in terms of the number and characteristics of new tariff plans.

When compared with the basic herding setting defined in the previous section, we see that search frictions or their absence, lock-in effects or preference for diversified information, and customer education or learning bounds, could all be respectively assumed to bias the information gathering process and demand of DMs in favour of the current or the previous setting, respectively. We illustrate the implications derived from these effects by comparing the information acquisition incentives and the resulting demand functions of DMs in both a frictionless environment and the $H_{0.4}(1s|2g/10g)$ case.

Figure 6 compares both transition settings and the resulting guaranteed demands, which represent the probability that the second characteristic of the

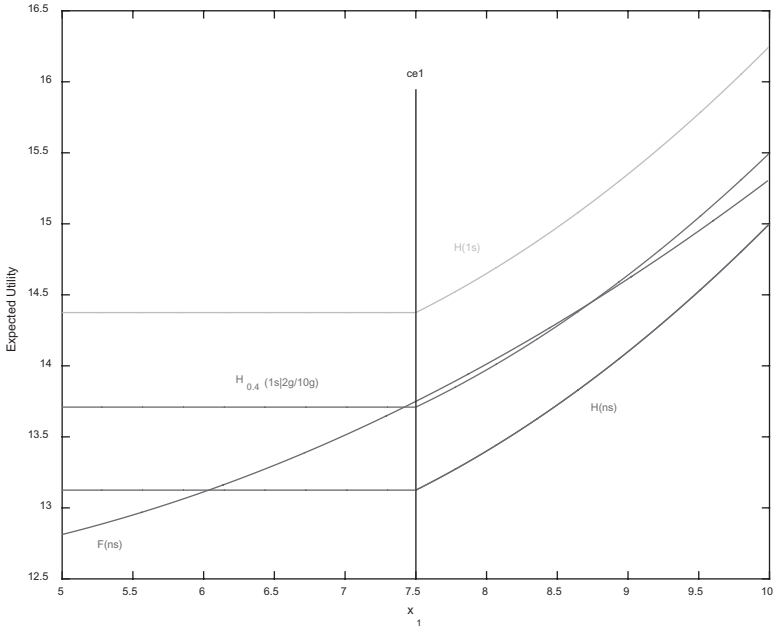


(a) Frictionless transition between products with a risk-neutral utility function

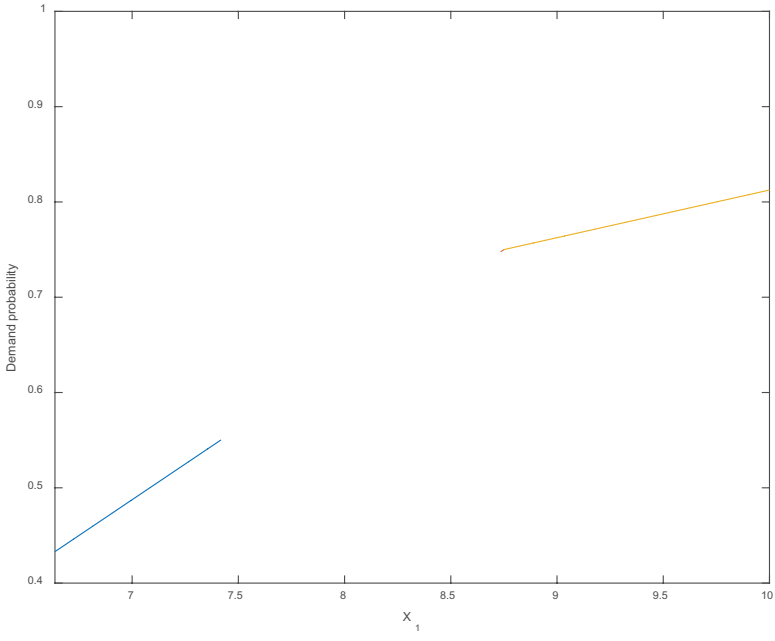


(b) Guaranteed demand function for all $x_1 > 6.6368$

Fig. 6. Information acquisition incentives, transition frictions and guaranteed demand.

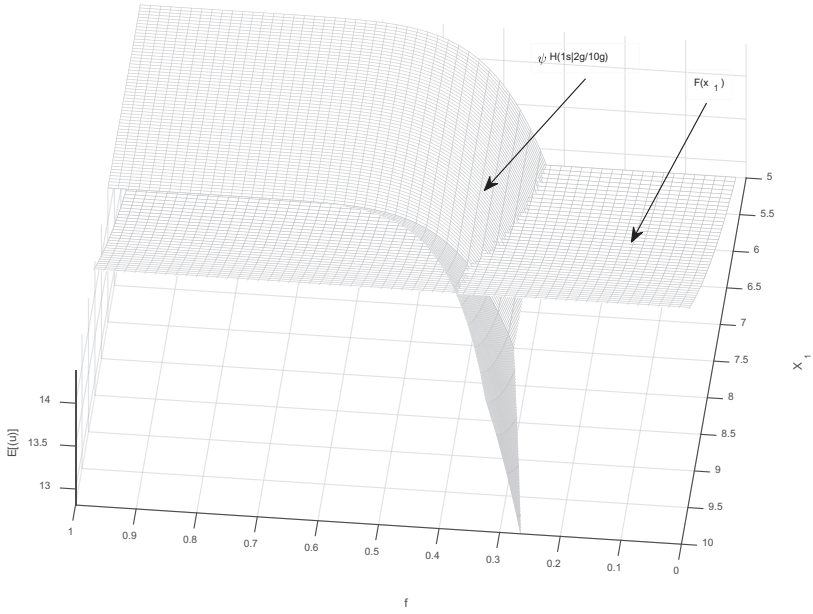


(c) Transition frictions for the $H_{0.4}(1s|2g/10g)$ case with a risk-neutral utility function



(d) Guaranteed demand function determined by the threshold values of the $H_{0.4}(1s|2g/10g)$ case

Fig. 6. (*Continued*)



(e) Transition frictions for the $\psi(10,2,f)$ binomial with $f \in [0,1]$ and a risk-neutral utility function

Fig. 6. (*Continued*)

signalled product provides a higher utility than the certainty equivalent one given the first characteristic guaranteed by the signalling firm to the DM. That is, guaranteed demands account for the probability of $x_2 \in X_2$ such that $u_2(x_2) > E_1 + E_{(2|\theta=1)} - u_1(x_1)$ for every $x_1 \in X_1$ observed by the DM in the unsignalled market. Note that this demand is equal to zero for realizations of $x_1 < 6.6368$, which corresponds to the threshold value of the first characteristic in the signalled market. We have also provided a general overview of the friction effect that guarantees the prevalence of mediocre products within the unsignalled market in Fig. 6(e).

In this latter figure, we can observe the existence of different values of f such that mediocre products prevail over the signalled ones when the DM requires at least two out of 10 consumers to adopt the new products during the search process. It should be noted that the values of f warranting the prevalence of mediocre products increase as the DM requires a larger number of consumers to adopt the new products. That is, stricter adoption requirements must be met with higher subjective expectations regarding the success of the new product in order for DMs to shift between markets.

A direct application of the analysis presented through this section to the existence and prevalence of lock-in effects in real life settings is provided below.

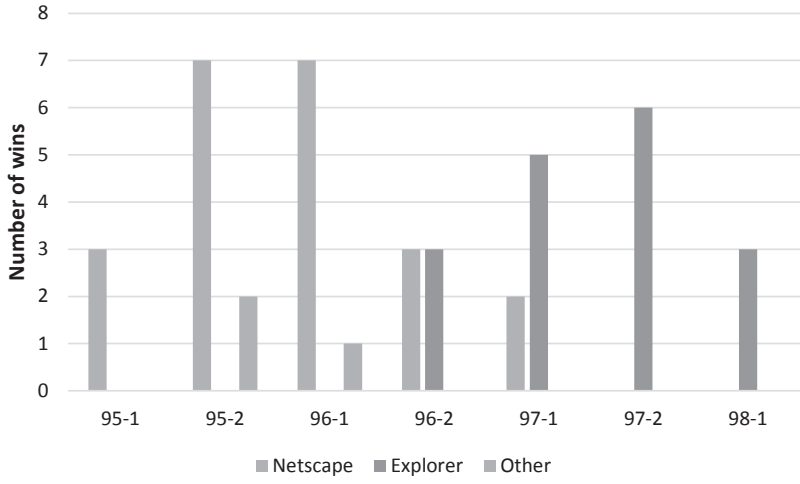
On the Netscape versus Internet Explorer case

We start by emphasising the two main conclusions that follow from the numerical simulations presented in Fig. 6.

(1) The first one has already been stated in Lemma 5.2. That is, the existence of search and matching frictions may force newcomers to improve upon very high characteristic values of x_1 displayed by the set of incumbent products in order to enter the market with a set of technologically superior products.
(2) The second one is the fact that a set of mediocre products offered by the incumbent may survive the entry of technologically superior ones, an equilibrium phenomenon that worsens with the strength of the frictions. That is, if the DM observes a characteristic x_1 in the unsignalled market located within a given interval from the ce_1 value, then he may have an incentive to remain within this market independently of the technological improvement introduced by the signaling firm. In this case, frictions constitute such a drawback for the DM that the higher value of $E_{(2|\theta=1)}$ expected within the signalled market does not compensate for their negative effect on his information gathering process. Once again, this occurs despite the signalling firm guaranteeing a product with a characteristic x_1 at least as high as the one observed in the unsignalled market. On the other hand, the $E_{(2|\theta=1)}$ and guaranteed x_1 effects *may* prevail over the search frictions if relatively high x_1 realizations are observed, leading to the information gathering reversals described in Lemma 5.2.

One of the most famous cases directly related to the lock-in literature was that of Netscape versus Internet Explorer within the antitrust proceedings of the United States government against Microsoft, a summary of which can be found in Liebowitz and Margolis (2001). The main argument put forward by the government was that the inclusion of Internet Explorer within Microsoft's operating system foreclosed the capacity of Netscape to generate market share. Liebowitz and Margolis (2001) argued that this was not the case and presented in Figs. 7 and 8 (which we have adapted to the current paper) as data validating their argument, i.e., that the best browser from January 1997 onwards took over the market. Figure 7 represents the number of wins achieved by each browser on a biannual basis from January 1995 to January 1998, while Fig. 8 describes their respective market shares within the January 1996–July 1997 period.

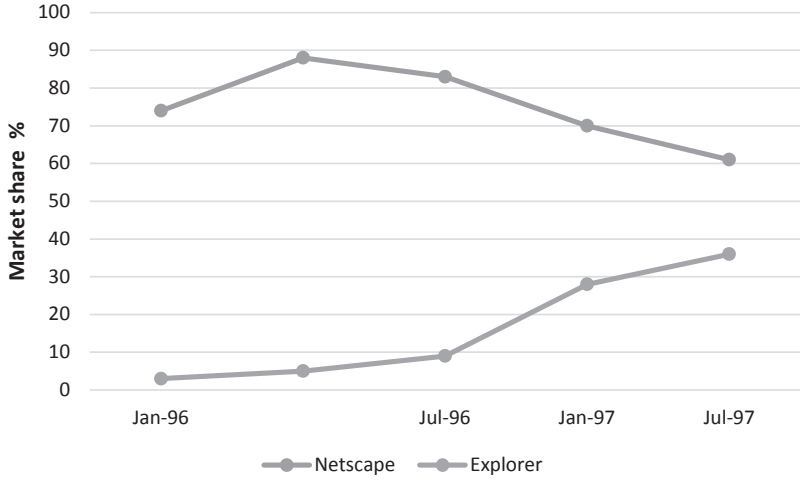
Let us note that the interpretation of the data made by Liebowitz and Margolis (2001) provides a plausible explanation to the competition process taking place between Netscape and Internet Explorer. However, we will use our model to provide an alternative explanation to this story. We will argue that DMs, freely



Source: Figure 8 in Liebowitz and Margolis (2001)

Fig. 7. Number of wins achieved by each browser, 1995:1–1998:1.

endowed with Internet Explorer in their computers, which was inferior to Netscape, did not have sufficient incentives to shift to the superior option. Indeed, if Internet Explorer covered the basic web surfing functions to an acceptable degree, the time and knowledge required for the users to fully exploit the superior qualities of Netscape — beyond the most important one of providing a reliable access to internet — may have prevented them from shifting between browsers. Note that



Source: Adapted from Fig. 9 in Liebowitz and Margolis (2001)

Fig. 8. Browser market shares, January 1996–July 1997.

these superior qualities remain unknown when making the shift between browsers and DMs can only (credibly) expect Netscape to perform better than Internet Explorer.

It should be emphasised that direct learning costs imposed on the DMs would cause the same type of shift in the function $H(x_1|\theta = 1)$ as the friction cases that we have described through this section. That is, we could interpret the refusal to shift from explorer to netscape as a case of passive innovation resistance (Heidenreich and Spieth, 2013), where consumers consider the (subjective) costs derived from downloading and comparing a browser that provides the same basic utility in terms of web surfing functions than the one already installed. In this regard, we could also consider the fact that browsers direct consumers to different predetermined start-up pages, to which (based on a 1998 survey) they grew so accustomed that were rarely modified (Liebowitz and Margolis, 1995). That is, other than the subjective utility that a consumer may derive from the start-up website, this fact can be interpreted in terms of the passive resistance exhibited by DMs when faced with modifications of a given *status quo*.

However, as the main justification for our argument, we will make use of the data provided by Liebowitz and Margolis (2001) and presented Figs. 7 and 8. We have left aside the fact that Internet Explorer was provided freely while Netscape had to be initially purchased, a policy abandoned by Netscape as they started losing market quota (Liebowitz and Margolis, 2001). Note how, despite being a clearly superior browser in January 1996 and being equally valued halfway through the year, Netscape started experiencing a decline in its market share somewhere in between January and July 1996. The rate of decline increased during the second half of the year. Note that Netscape experienced this decline during a period in which the household penetration rate of personal computers experienced a particular large increase, as Table 2.12 in Grant and Meadows (2014) illustrates.

There are two potential explanations for this shift in market share trends. The first one would state that DMs had the capacity to foresee the quality improvement that was going to be experienced by Internet Explorer over the course of the following year and chose accordingly despite the information available in the market when making the choice. On the other hand, it could be argued that a large amount of new consumers were endowed with a browser that satisfied their basic internet requirements. The browser was recognised to be inferior to the alternative but the consumers did not have sufficient incentives to modify their choices, a plausible outcome given the results derived from our model.

The results obtained can therefore be considered as second degree path dependence in terms of Liebowitz and Margolis (1995), i.e., a suboptimal decision is made due to imperfect foresight on the side of the consumers, who were unwilling to shift to Netscape and explore its full potential. However, given the (equilibrium)

uncertainty existing in the market regarding the unknown evolution of a product and the very same nature of path-dependence (Stock and Schulz, 2015), these results could even be interpreted as third degree path dependence if the expectations of the consumers, on which their risky decisions are based, were fully correct.

To summarize, we have illustrated how their sets of available products may provide incumbent firms with a significant advantage over newcomers due, among others, to lock-in, bandwagon, network and reputation effects. Bandwagon and network effects are also formally discussed and incorporated by Malerba *et al.* (2003) in their behavioural evolutionary model of demand. However, these effects have been assumed to be implicitly defined within a subjective cumulative probability function, $\psi(m, l, f)$, lacking the explicit dynamic diffusion properties that these effects generally account for (Geroski, 2000). The following section studies the influence that network (bandwagon and reputation) effects and the corresponding diffusion processes have on *the introduction* of technologically superior products within a given market.

Technology Diffusion and Network Effects

The third type of setting analysed considers the market *introduction* of technologically superior products from the point of view of the supplier. That is, we are going to use our model to compute the expected prevalence of a given product in the market when information regarding the existence of a technologically superior product spreads across consumers following different diffusion processes.

Our change in perspective is motivated by the increase in the information assimilation and computational requirements that should be imposed on the DMs so as for them to be able to foresee the different diffusion processes that may arise after the introduction of a technologically superior product in the market. In this regard, when analysing the adoption of a new product within their demand-based model, van den Ende and Dolfsma (2005, p. 87) assign the decision-making role to a firm. The authors justify their choice as follows: "Final consumers are different from firms which choose to acquire a product, even if it is the same product. Decision-making processes of firms are more rational, as for firms more time lapses between a decision and the actual behaviours. Still, the perceived rationality of decision-making processes in firms should not be overestimated."

Additional intuition justifying our change in perspective follows from the fact that, after all, it is firm's managers the theoretical entities who, based on their available information, decide whether or not to introduce a given technology in the

market, a fact that the recent literature on knowledge economics and management recognises and accounts for, see Foray (2004) and Holsapple (2003) for a review of the respective literatures.

The current setting could be alternatively interpreted as the *acquisition* of technologically superior products by highly sophisticated DMs, i.e., users in the sense of von Hippel (1988). If we were to follow this alternative interpretation, it should be emphasised that the psychological and sociological characteristics of the environment affecting the preferences of and choices made by DMs change as the product evolves, a problem accounted for in marketing and sociology, but seldom by the economic literature, with exceptions emerging from its evolutionary branch such as Aversi *et al.* (1999), Rogers (2003), Fatas-Villafranca and Saura-Bacaicoa (2004), and Malerba *et al.* (2007), among others.

Moreover, the evolutionary economics literature has also started to delve into the strategic choices directly faced by firm's managers within the existing markets for technology and knowledge, see Arora *et al.* (2001a).

Therefore, diffusion processes and network effects will be considered from the point of view of a manager deciding whether or not to introduce a technologically superior product in the market-based, for example, on the market share or the compatibility with the products developed within other market sectors that the product is expected to attain within a given time frame. In this case, the expectations of DMs (managers) regarding the type of diffusion process under consideration and their forecasted evolution of possible complementary or substitute products become extremely important. The essential role played by the careful management of the multiple diffusion barriers that must be overcome when introducing a new product has been emphasised by Talke and Hultink (2010).

The current setting has been developed to illustrate an important point made by Geroski (2000) when analysing the main patterns generally believed to determine the behaviour of diffusion processes and the crucial importance that initial conditions and choices have on the evolution of the technological diffusion path: "When the initial choice between A and B is made quickly and clearly and when A is clearly superior to the existing technology, then diffusion is likely to be rapid (quick and decisive decision-making will quickly stampede the herd into action). If, however, these early choices are muddled, then the processes which generate and swell an information cascade are likely to be fragmented and weak", see Geroski (2000, p. 620). Moreover, diffusion processes should be determined both by the characteristics of the consumers and those of the products being considered, a point recently highlighted by Langley *et al.* (2012).

We will consider two main diffusion (epidemic) processes, widely employed both in biology and by the evolutionary economics literature, used by Geroski (2000) to analyse the apparently slow speed at which firms adopt new

technologies. One of them is based on a central diffusion source while the other relies on a word of mouth non-centralized communication process.

(i) Out of a normalized population of potential users, denote by $\Psi_a(t)$ the percentage of DMs who have either adopted the technologically superior product at time t or are aware of its existence, while those who have not yet adopted it or are unaware of its existence are defined by $\Psi_n(t) = 1 - \Psi_a(t)$. Assume that information is transmitted from a central source, reaching a percentage α of the population who has not yet adopted the technology or is unaware of its existence at time t. If information is received over the time interval Δt, adoption or awareness increases by an amount $\Delta\Psi_a(t) = \alpha\,(1 - \Psi_a(t))\,\Delta t$ during this period. The solution of this difference equation as $\Delta t \to 0$ is given by (see any textbook on the subject, for example, Braun (1983)):

$$\Psi_a(t) = 1 - e^{-\alpha t}, \quad t \in [0, T]. \tag{14}$$

Geroski (2000) relates this type of diffusion process to the transmission of information regarding the existence of, for example, a new hardware. However, he emphasises the fact that this type of process may not be accurate when accounting for the information flows about the associated software. In this case, a word of mouth information diffusion process must be considered.

(ii) Denote by $\Xi_a(t)$ the number of DMs who have either adopted the technologically superior product at time t or are aware of its existence. In this case, $\Xi_a(t)$ is taken out of a total population of N DMs composing the market. Assume that each adopter aware of the existence of a technologically superior product contacts a non-adopter or unaware DM with probability β. The probability that contact is made with any non-adopter (unaware DM) at time t is given by $\beta\Xi_a(t)$. Thus, the percentage of adopters (aware DMs) increases over the time interval Δt by the amount $\Delta\Xi_a(t) = \beta\,\Xi_a(t)\,(N - \Xi_a(t))\,\Delta t$. The solution of this difference equation as $\Delta t \to 0$ is given by

$$\Psi_a(t) = \left(1 + \left(\frac{1}{\Psi_a(0)} - 1\right)e^{-\beta N t}\right)^{-1}, \quad t \in [0, T], \tag{15}$$

where $\Psi_a(0)$ is the proportion of adopters or aware DMs existing at time zero.

Consider now the effects that different types of diffusion processes may have on the information acquisition and choice behaviour of DMs. In particular, a sophisticated DM must decide whether or not to proceed with the introduction of a technologically superior product based on the factors defining the speed and type of diffusion process under consideration. Following a similar intuitive description to the one used in the search and matching frictions scenario, the information gathering transition between markets will be based on the

following comparison

$$\begin{aligned} &\text{either } F(x_1) > \Psi_a(t)H(x_1|\cdot) \\ &\text{or } F(x_1) < \Psi_a(t)H(x_1|\cdot), \quad t \in [0, T]. \end{aligned} \tag{16}$$

Clearly, different dynamic forecasts resulting from different diffusion processes would lead to different threshold reference values and to products being accepted or rejected at a given point in time depending on their expected (market) spread velocity. That is, relatively faster spreads imply that $H(x_1|\cdot)$ surpasses $F(x_1)$ for all $x_1 \in X_1$ within relatively shorter periods of time.

An obvious alternative interpretation of $\Psi_a(t)$ could be made in terms of the expected compatibility of the product under consideration with the set of complementary (and substitute) products existing within other market sectors. In this regard, Arora *et al.* (2011b) emphasise the importance that markets for technology have for the strategic management of firms.

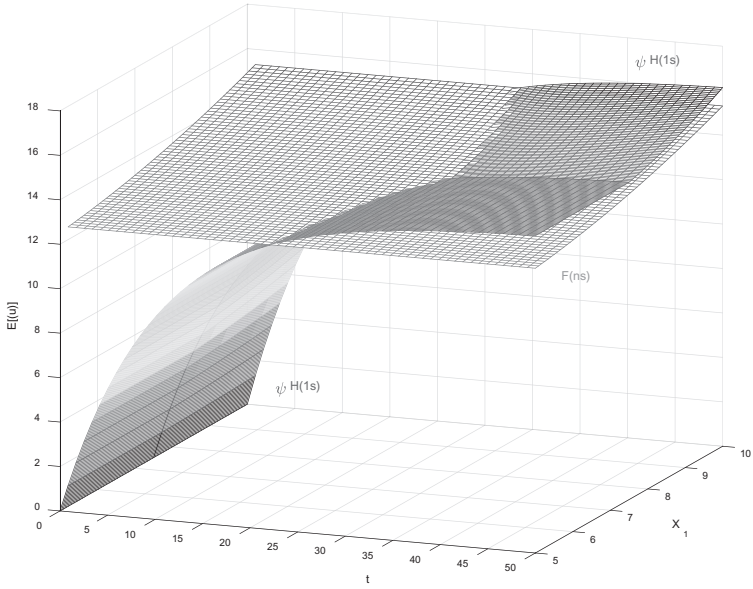
Finally, note that the current setting provides an alternative theoretical framework to the generalized Polya urn decision theoretical environment defined by Kornish (2006) when analysing the effect that different network and diffusion processes have on the choice and timing of technology.

Numerical simulations: diffusion and network effects

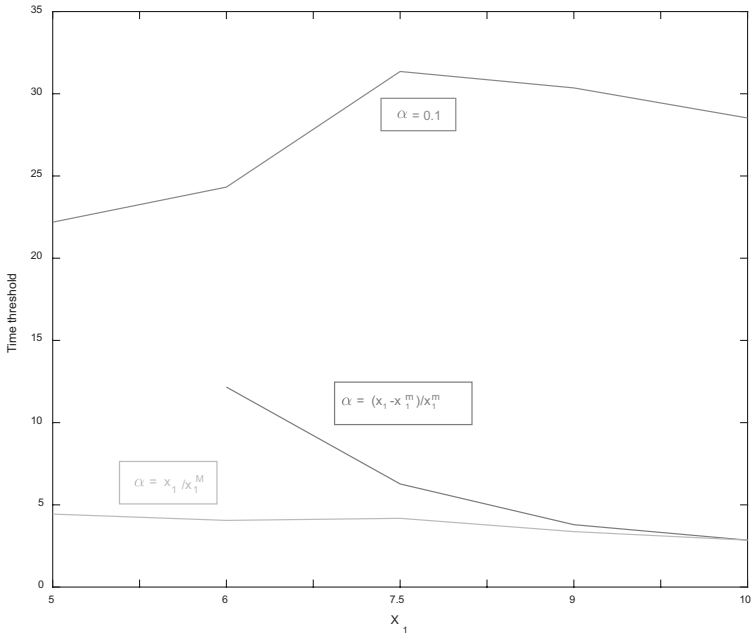
The numerical simulations presented in Fig. 9 illustrate how different expected diffusion patterns determine the decision of whether or not to introduce a technologically superior product in the market. Note that these figures constitute a dynamical version of Figs. 4 and 5. Figure 9(a) provides an example of network and diffusion effects with a centralized source. $\Psi H(1s)$ represents the original function $H(1s)$ weighted by a $\Psi_a(t)$ diffusion process with a coefficient $\alpha = 0.1$ and a duration of 50 time periods. On the other hand, Fig. 9(c) illustrates network and diffusion effects with (word of mouth non-centralized) multiple sources. In this case, $\Psi H(1s)$ represents the original function $H(1s)$ weighted by a $\Psi_a(t)$ diffusion process with coefficients $\beta = 0.1$, $N = 10$, $\Psi_a(0) = 0.01$ and a duration of 50 time periods.

Thus, depending on the expected type of diffusion process under consideration, some firms may decide to introduce a product or wait for further suppliers to take on the technology and then proceed. Highly educated consumers in the sense of Eng and Quaia (2009) may be assumed to promote faster spreads and guarantee higher profits during longer periods of time due to educational lock-in and brand loyalty effects. As a consequence, subjective forecast differences across DMs regarding the evolution of $\Psi_a(t)$ would be responsible for the emergence and stability of technological niche markets within the current theoretical setting.

It also follows from Figs. 9(a) and 9(c) that attaining the awareness of a large enough number of consumers is a relatively slow process, which may result in the

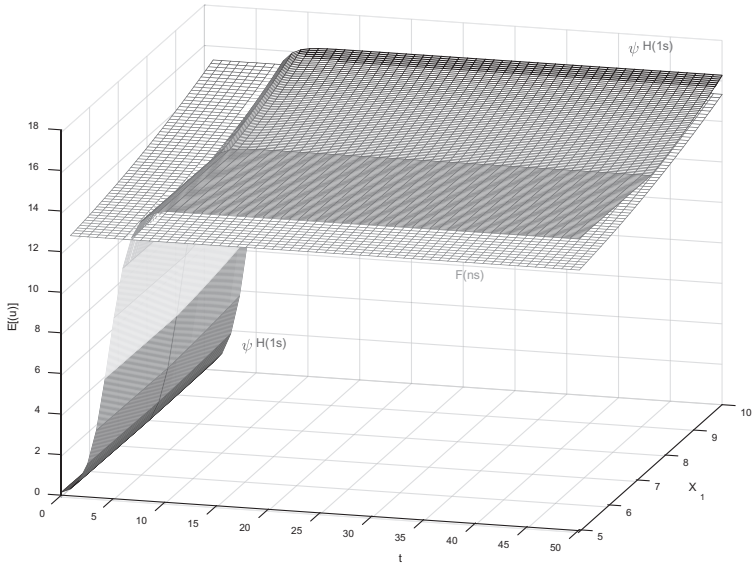


(a) Transition incentives with a centralised information diffusion source and a risk-neutral utility function

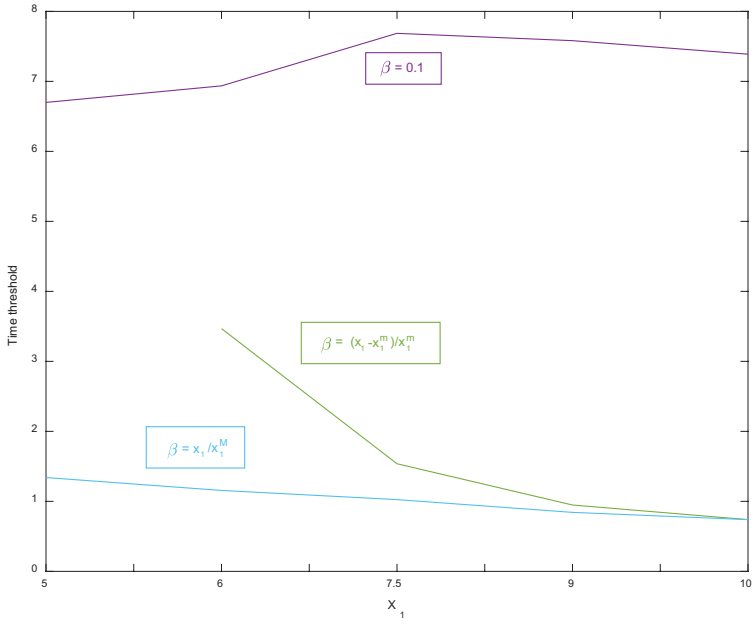


(b) Time threshold values with a centralised information diffusion source and varying α values

Fig. 9. Diffusion of information and time thresholds.



(c) Transition incentives with non-centralised information diffusion sources and a risk-neutral utility function



(d) Time threshold values with non-centralised information diffusion sources and varying β values

Fig. 9. (*Continued*)

prevalence of suboptimal products. However, this effect can be substantially mitigated when the speed of information transmission is increased. To illustrate this possibility, we have simulated two additional scenarios where the dynamic behaviour of the information transmission process is determined by the initial realisation observed by the DM.

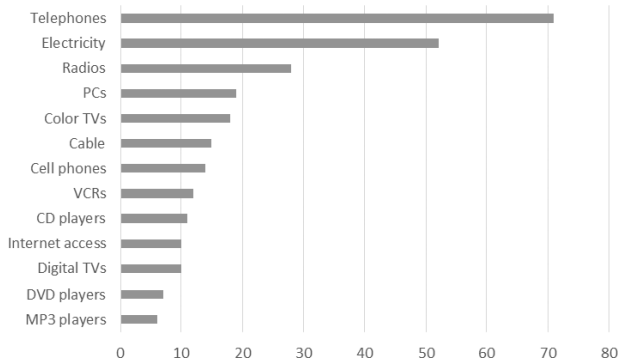
The first one assumes that the α and β parameters determining the speed of information transmission are given by $(x_1 - x_1^m)/x_1^m$. That is, given the fact that the domain of $X_1 \in [5, 10]$, we have simply normalised the speed of transmission based on the initial realisation. The second scenario increases the transmission speed further by assuming that the α and β parameters are given by $(x_1)/x_1^M$. The number of time periods required for $F(x_1) = \Psi_a(t)\, H(x_1|\theta = 1)$ in all three scenarios with a centralised and a non-centralised source is represented in Figs. 9(b) and 9(d), respectively.

The numerical simulations based on these information transmission rates illustrate how, in both the centralised and non-centralised cases, mediocre products take longer than the relatively optimal ones to be replaced. Clearly, replacement is faster when the process of information transmission is non-centralised. When $\alpha = \beta = 0.1$, we observe how a mediocre product can prevail the longest in a dynamic environment, while relatively optimal products are also able to resist long periods before being replaced.

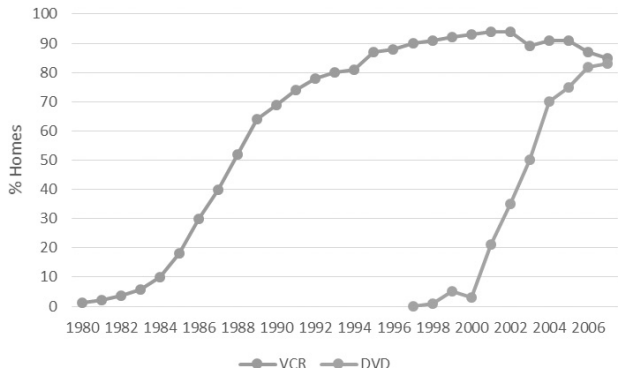
Note how as the speed of information transmission increases, relatively optimal products are replaced at a faster rate than the relatively suboptimal ones. The intuition for this result follows from the guarantee of improving upon the initial characteristic of the incumbent product issued by the newcomer firm. Thus, relatively optimal incumbent products should be guaranteed to be improved upon by the newcomer, leading to their almost immediate replacement with a non-centralised information source.

Policy implications

The empirical economics literature has documented the substantial increase in the speed of adoption and diffusion taking place among recent technologies (Thierer and Eskelsen, 2008; McGrath, 2013). Figure 10, consisting of two of the multiple exhibits presented by Thierer and Eskelsen (2008) has been introduced to illustrate this fact. When considering the positive effects of diffusion, the literature generally focuses on the rate of diffusion across countries, whose increase is related to that in human capital and the adoption of predecessor technologies (Comin and Hobijn, 2004). At the macroeconomic level, path dependence can be integrated as part of the evolutionary process of technology, which is not necessarily the result of market failures (Tassey, 2016).



(a) Number of years it took for major technologies to reach 50% of homes
Source: Exhibit 4 in Thierer and Eskelsen (2008).



(b) Household penetration of VCR and DVD players
Source: Exhibit 47 in Thierer and Eskelsen (2008).

Fig. 10. Increase in the speed of adoption and diffusion of technologies.

However, as David states when describing the main policy implications derived from path dependence.

"One thing that public policy could do is to try to delay the market from committing the future inextricably, before enough information has been obtained about the likely technical or organizational and legal implications, of an early, precedent-setting decision." (David, 1997, p. 41).

"The 'first best' public policy role in these matters, therefore, is not necessarily the making of positive choices, but instead the improvement of the informational state in which choices can be made by private parties and governmental agencies." (David, 1997, p. 42).

The results obtained from the simulations are in line with the suggestions of David regarding the positive effect that an increase in the amount of information

resulting from public intervention should have in favouring the choice of the best technology available. However, a word of caution is due given the fact that the public system is also subject to biased lock-in phenomena and private interests (Walker, 2000; Briggs *et al.*, 2015). These latter authors have suggested that the negative consequences from such a drawback could be weakened as awareness improves. In this regard, the increase in the speed of information transmission that has lead to much faster diffusion processes could be seen as a positive force in the elimination of suboptimal lock-in phenomena. We should also keep in mind the substantial increase in the amount of advertising, particularly in online environments, documented by Thierer and Eskelsen (2008).

Thus, given the large amount of information — not all necessarily unbiased — available nowadays, the manipulation of the choices made by the DMs, who must actually drive the shift between technologies, arises as an important possibility. For example, consumer innovativeness can be implemented to the technological diffusion process in order to identify the resulting opinion leaders (Shi and Fernandes, 2014), whose subjective product choices will determine those prevailing in the market. This research area has received a renewed interest given the inability of consumers to distinguish the quality of information available in the market (Akerlof and Shiller, 2015).

In this regard, Dolfsma and Leydesdorff (2009) emphasise the pervasive effects of lock-in and exemplify how if network externalities among adopters are reinforced by the market, then the development of a new generation of technologies may be irrelevant to the techno-economic system that prevails. Together with markets and technology, these authors consider political decision-making as a third selection mechanism that may allow for breaking-out from a given technological trajectory, highlighting the substantial role played by institutions in the process (North, 1990). Though the explicit introduction of DMs brings our paper closer to theirs, there exists a fundamental difference between both. That is, Dolfsma and Leydesdorff (2009) state that their main argument does not depend on assumptions about the characteristics of a technology, nor the extent to which agents' knowledge is perfect or complete. Besides, they do not account for the possibility of DMs responding to their (social) environment, while our model implicitly allows for this type of scenario.

On the emergence and stability of technological niche markets

The emergence and stability of technological niche markets (introduction and prevalence of a product) could be intuitively justified in several ways within the current environment.

First, as Malerba *et al.* (1999, 2001) illustrate, the main advances in component technologies driving the evolution of the computer industry were developed by newcomer firms that managed to survive by supplying experimental consumers in technological niche markets. In this regard, Malerba *et al.* (2003, 2007) highlight the fact that incumbents have been shown to be subject to cognitive biases and organisational factors that play a major role in accounting for the fatal lag in their response when the new technology succeeds in getting a foothold. That is, an incorrect estimation of $\Psi_a(t)$ and the corresponding gains derived from introducing a technologically superior product by the incumbent firm, i.e., miscalculating the payoffs and, therefore, the stability of the technological niche market, could lead to the creation of stable technological niche markets by a newcomer with a different estimation of $\Psi_a(t)$ and its dynamic evolution. Accounting for network and bandwagon effects (as our DMs are assumed to do) requires defining several potential diffusion processes subjectively, which may greatly differ across firm managers and significantly modify their expected payoffs and subsequent decisions.

Second, the existence of vintage effects (Bohlmann *et al.*, 2002), implies that later entrants can exploit the improved technology introduced previously to decrease their costs and improve their quality relative to that of the pioneer signalling firm. Bohlmann *et al.* (2002) show that pioneers in categories with large vintage effects generally have lower market shares and higher failure rates. They also illustrate empirically that pioneers do better when product variety constitutes the most important category for the DMs and worse when quality is considered to be the most important category. In this regard, we could argue that differences in the communication and diffusion patterns determining $\Psi_a(t)$ may arise depending on the type of attribute under consideration, as Geroski (2000) did at the product level when defining the hardware versus software example described above.

Third, if instead of using the percentage of potential adopters as the main variable defining the diffusion equation, we use the technological development level of either competitors or subsidiaries, we could allow for a formal representation of the strategic interactions existing behind the formation of markets for technology (Arora *et al.*, 2011b). Similarly, we could assume that $\Psi_a(t)$ represents the expected development of the technological requirements that must be mastered by a firm or its competitors in order to enter a market. Both these interpretations must be based on the heterogeneously formed expectations of firm's managers, which will result in different $\Psi_a(t)$ being considered when defining the strategies of the corresponding firms.

Finally, note that $\Psi_a(t)$ could also be assumed to reflect the influence that different types of policies have on the decision making processes (and incentives) of both firm's managers and consumers. For example, fiscal policies could be used to discriminate among products or to establish an early product demand base in

order to guide the market in a particular direction. Moreover, sectoral characteristics may also determine the adoption process of technological change. These features would range from the capacity to reap the rewards arising from technological progress, which varies across technological regimes, to the existence of intermediaries between the supply and demand sides, such as doctors within the market for prescription drugs. Clearly, these and many other environmental features may be included to account for possible changes in the behaviour of $\Psi_a(t)$ and their effect on the evolution of technological niche markets.

Conclusion and Future Research Directions

The current paper has presented a decision theoretical model of demand for technologically superior products that provides a compatible perspective with the results obtained by the behavioural evolutionary economics literature.

We have illustrated how consumers may stick to an inferior product when market frictions or their own expectations dictate them to do so, despite the newcomer firm credibly guaranteeing an improvement upon the main characteristics of the incumbent product. As a result, we concluded that the prevalence of a suboptimal technology can be the result of the correct choice being made at a given point in time.

In order to describe the main implications of our decision model, we have revisited the Netscape versus Internet Explorer case study analysed by Liebowitz and Margolis (2001) and illustrated how the Netscape browser could have been displaced from the market by Internet Explorer despite being considered an initially superior alternative and recognised as such by the consumers.

We have also analysed the consequences derived from the existence of path dependence phenomena from a dynamic perspective by explicitly accounting for the emergence of network effects that may take place after firms signal the availability of a technologically superior set of products. In particular, we have computed the expected prevalence of a given product in the market when information regarding the existence of a technologically superior product spreads across consumers following different diffusion processes. Among the results obtained, we observed how as the speed of information transmission increases, relatively optimal products are replaced at a faster rate than the relatively suboptimal ones. Thus, given the large amount of biased information available nowadays, the manipulation of the choices made by DMs arises as an important possibility among the potential outcomes that can be derived from the model.

In this regard, it should be noted that the information acquisition incentives of DMs have been defined through their expected search utilities, which, at the same

time, define implicitly the revenues expected to be obtained by firms. That is, given the available distribution of product characteristics that may be displayed by a firm, its expected revenues depend on its ability to provide the characteristics required by the DMs. In this sense, we have assumed that market signals correspond to truthful fully credible reports. However, reputation and strategic communication problems, such as cheap talk, would arise if they were not. Thus, the strategic nature of the information transmission process and its effect on the subsequent choices made by consumers could be considered for an immediate extension of the model presented in the paper.

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