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Herd Behaviour, Strategic Complementarities and Technology Adoption

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Abstract

In technology adoption, herd behaviour can lead to a suboptimal outcome. An example is given by Choi (1997): it is a model of technology choice under uncertainty where herding arises because of strategic complementarities and risk aversion. It causes a positive experimenting bias against the adoption of a more efficient (in terms of expected value) technology. We introduce in his model an additional element upon which firms base their technology decision: the economic environment. We investigate how this additional source of uncertainty can affect herding and so the efficiency of the technology choice. The result is that, under certain conditions, the experimenting bias decreases and in the limit it is possible to induce firms to experiment with the new technology thus improving social welfare.

Keywords: herding, information and network externalities, public information, social learning, technology adoption.

JEL Classification: D62, D80, D83, L15.

1 Introduction

Herding, in the traditional sense, is the phenomenon by which "everyone does what everyone else is doing, even when their private information suggests doing something quite different", (Banerjee, 1992). In economics and in general in everyday life, people's decisions are influenced by those of others around them, i.e., they make their own decisions looking at the decisions made by previous decision makers. Herd behaviour and informational cascades have been used to explain a variety of social phenomena, such as manias, panics, financial and currency crises, bank runs, etc., as well as other economic phenomena like the failure of agents to adopt the most efficient technology.[1]

A fundamental mechanism in herding models is social learning: when a person learns from other's behaviour, i.e., her action or her words, she does so because the person's behaviour is based on information she has about a state of nature that is of interest to everybody. The process of social learning is the diffusion of this private information or private belief through the observation of the actions taken by the others. Private beliefs are defined as agents' subjective probabilities about the state of nature. Each agent observes a signal about the state of nature and so updates his beliefs using Bayes' rule.

Herding models differ according to the reason why people join the herd. It is possible to distinguish between herding models based on informational externalities, and herding models explaining herd behaviour in terms of strategic complementarities.

The pioneering papers studying this topic are Banerjee (1992), Bykhchandani, Hershleifer and Welch (1992) and Scharfstein and Stein (1990). They are based on informational asymmetries and differ mainly on the information structures that they assume. In particular, they are models of sequential choice in which agents can observe the actions made by their predecessors but not the information upon which they decided. Herd behaviour arises because each agent suspects that her predecessors had private information and tries to free-ride on it. Players cannot decide to delay their decisions

[1] A cascade occurs when all players, independently of their own information, undertake the same action at the same time, say, time one. Indeed Chamley (2002) argues that it is important to distinguish between the two phenomena: while in a cascade nothing is learned, in a herd in general social learning takes place, here all agents choose the same action in all periods but there is the possibility that some agents could choose a different action. "One may say that a cascade is an *ex-ante* concept, while a herd is found out *ex-post*" (Chamley, 2002, p. 60).

since the order of choice is exogenously given. This tendency to try to use the information contained in the other people's decisions makes each person's decision less responsive to her own information and, in turn, less informative to others; Banerjee speaks about a negative externality, called "herd externality", that the person joining the herd inflicts on the rest of the population.

This literature points out the inefficient outcomes that may arise in a herding setting, i.e., herding may lead players to adopt an action which ex post turns out to be suboptimal. However, there are models where herding can act as an incentive scheme and therefore increase efficiency. Interesting examples are Chamley (1997), who analyses an investment decision problem with endogenous timing and Melissas (2003), who studies a reversible technology choice under uncertainty. In a nutshell, the authors, introducing some costs (a cost to delay in the first model and a switching cost in the second one), show that the expectation of future herding can lead to the most efficient outcome.

The herding models reviewed so far are characterized by the fact that individual payoffs are independent of the actions of the others, i.e., there are no strategic complementarities, thus agents exhibit only backward-looking behaviour. In many settings, in addition to the informational externalities it is important to incorporate payoff externalities. Dasgupta (2000) states that with strategic complementarities, agents need to look at the actions of their predecessors as well as those of their successors. Then, agents exhibit both backward-looking (learning) and forward-looking (strategic) behaviour.

An important setting characterized by strategic complementarities, where herd behaviour can cause a suboptimal outcome, is the technology adoption problem. An interesting example is given by Choi (1997): this is a model of technology choice under uncertainty where N firms sequentially choose between a safe old technology and a risky new one. The author investigates how informational externalities interacting with network externalities induce herd behaviour and create biases against the adoption of a new technology. His main result is that the second user turns out to be the pivotal one in the adoption process, because once the first user has chosen the old technology, if the second user does not choose the new one, then the latter will never be experimented. This outcome is due to the existence of a positive bias against the adoption of a new and more efficient, in terms of expected value, technology.

Referring to herding models characterized by strategic complementarities, in particular to Dasgupta (2000) and Corsetti, Dasgupta, Morris and

Shin (2000),[2] the purpose of our paper is to try to generalize Choi's results by introducing another element upon which firms base their technology decision: the economic environment. We investigate how an uncertain economic environment can affect herding and consequently the efficiency of the technology choice.

In order to explain what the economic environment is, we refer to Adner (2003). He considers the relationship between consumers' valuation of performance improvements and technology development over the technology life cycle. He states that the technology final performance is determined by two elements: the "technology maturity", represented by the level of technology performance and the "demand maturity", represented by consumers' valuation of the technology, or in other words, consumers' preferences. Thus, it can be argued that the economic environment, represented by the "demand" environment affects the final performance of a technology and so it plays an important role in the decision making. Our model provides a simple framework to analyse the role of the demand environment in affecting herd behaviour and determining firms' innovation incentives.

Alternatively, in line with David (1986), the uncertain economic environment we refer to, could be explained as uncertainty about government's policy. In fact, since technology diffusion represents an overarching policy goal, governments can affect firms' decisions by stimulating the implementation of a particular technology.

It will be shown that Choi's model can be read as a particular case of this model and that under certain conditions it is possible to make the technology choice independent of the other users. In particular, the main result is the possibility to make smaller the bias against the adoption of a new and superior technology, obtaining a better outcome in terms of social welfare. This last result is also in accordance with Liebowitz and Margolis (1994) who find very little support for the idea that a less efficient technology can conquer the market and lock out a more efficient one. In their words, "we are aware of no compelling examples of markets failing in the sense that the "wrong" choice of network, among feasible alternatives, was made".

[2] In these models, decisions are determined by the actions taken by other agents and by their information about a state of the world that is of interest to everybody. They are sequential games where N risk neutral agents choose whether to invest or not in the first model and whether to speculate on the currency or not in the second model. Agents decide on the basis of the actions taken by their predecessors and on the basis of a private signal they receive about the state of the world. The authors discuss the equilibrium in terms of "trigger strategies", that is, in a nutshell, they find the critical levels of the signals that lead agents to choose the action independently of the others.

In particular, they refer to two famous examples: the Dvorak keyboard and the Beta videotaping. In fact, recent studies indicate that they were wrongly considered superior technologies locked out by QWERTY keyboard and VHS videotaping, respectively, given that the evidence does not support any relevant difference between them.[3]

The remainder of the paper is structured as follows. Firstly, some empirical support for the model is provided, pointing out the links with the technology adoption literature. Secondly, we introduce the analytical framework following and extending Choi's model: it is postulated that firms receive a public signal about the economic environment (symmetric information) changing the information structure of his model. We provide the equilibrium decision rule and we compare our results with Choi (1997). We finally analyse the equilibrium behaviours in terms of "trigger strategies". The paper concludes with a discussion of the results and of open issues.

2 A model of technology choice under uncertainty with network externalities

2.1 Related literature

Choi's model is about the problem of technology choice under uncertainty between a safe old technology and a risky new one which a sequence of firms has to face. The author investigates how informational externalities interact with network externalities inducing herd behaviour and creating biases against the adoption of a new technology.

This paper is also related to the network-externalities literature, whose seminal paper is represented by Farrell and Saloner (1985). They develop a model of technology choice in order to investigate whether standardization and compatibility can lead to a bias against the adoption of a better technology. In their words "we examine whether standardization benefits can "trap" an industry in an obsolete or inferior standard when there is a better alternative available" (p. 70). Standardization has, in fact, social benefits as well as social costs, since an industry could be reluctant to adopt a new and better technology because of the adjustment and coordination costs. They consider both a model with complete information, where this distortion does not take place and a better technology is always adopted, and a model with incomplete information where "excess inertia" takes place

[3] In accordance with this empirical relevance, Colla and Garcia (2004) present a different rationale for the absence of lock-ins.

and the new technology is not adopted even if adoption is favoured by both firms. They introduce uncertainty in the fact that the firm choosing first does not know whether it would be followed by the other firm in switching. They represent this uncertainty as incomplete information about the other firm's preferences.

Choi introduces another source of uncertainty that creates a bias against the adoption of the new technology. In particular, he considers as unknown the true values of the alternative technologies. This uncertainty can mainly represent uncertainty about their true productivities. He supposes that the adoption of a technology by any user reveals its true value thus creating an important informational externality for all subsequent users: in fact, once the new technology is adopted by anyone, the uncertainty is resolved.

In our model, we introduce an additional source of uncertainty by arguing that the economic environment plays an important role in the technology choice. Namely, we include in the current informational structure a stochastic public signal about the state of the world (the economic environment). In particular, it is assumed that once the new risky technology is experimented its intrinsic value is revealed, but the final net benefit becomes certain only some time after the adoption.

Referring to Adner (2003), we state that the final performance of a technology depends on two elements: the level of technology performance and consumers' valuation of technology in terms of their *willingness to pay*. He argues that there exists a threshold level of performance required by a consumer to accept the offer and beyond this level she can evaluate improvements in different ways: depending on consumers' preferences a new technology can succeed or fail. He provides several examples in which the "demand maturity" has been determinant in the final performance of a new technology. In the market for photolithographic printing equipment, the demand for increasingly finer resolutions has outpaced the rate at which resolution has improved; in such settings, where technology matures before demand, products providing the highest performance levels are most likely to succeed in the market. On the other hand, if demand matures before technology the outcome can be opposite, i.e., a superior technology can fail: in the market for computer microprocessors, for example, consumers prefer faster chips to slower ones, *ceteris paribus*, but beyond a certain level of speed, they prefer to trade-off speed for lower prices. In this case, firms adopting a less "sophisticated" technology are more likely to succeed. Thus, uncertainty about the demand environment affects firms' innovation incentives. It can also depend on the introduction of other complement technologies that facilitate the diffusion of a new technology. Think, for example, of the introduction of digital cameras and online music distribution: they created numerous and sizeable digital files that, in turn, increased the value to consumers of additional hard disk drive storage capacity.

Alternatively, the uncertainty about the economic environment can be interpreted as uncertainty about government's policy. In fact, as stated by Bar (1987), for technologies characterized by network externalities, standards play an important role: "analysts widely recognize that markets left to their own devices usually result in an insufficient degree of standardization, and induce losses of efficiency from an overall economic point of view", (p.10). Therefore, governments have the opportunity to increase welfare by affecting the standardization process. However, David (1986) points out that policy makers face three dilemmas. Firstly, "Narrow Policy Window Paradox" refers to the fact that, due to the increasing returns to scale, when different technologies compete, the adoption process can lead to lock in some technologies and lock out others in a brief time period. Consequently, "there may be only comparatively brief and uncertain windows in time" (David 1987, p. 210), i.e., a short period, for public policy intervention to be effective at reasonable costs. Secondly, "Blind Giant Quandary", refers to the fact that public agencies employed in developing standards have more power to affect the technology adoption when they know the least about it, and so they act as "blind giants", i.e., they do not know with certainty which technology to support. Finally, "Angry Orphans" refers to the firms that have chosen the now abandoned technology, and so they are stranded in specialized niches. Therefore, on the one hand, governments try to keep the policy windows open as long as possible in order to let the blind giants learn more about which standard is the good one; on the other hand, the higher the degree of standardization the higher the number of angry orphans. In our model, these "blind giants" would represent the uncertain economic environment in which firms choose.

Our model provides a simple way to incorporate and model this additional source of uncertainty. Moreover, in such a framework the final performance of the technology is not revealed just with the adoption, but later, thus being closer to the reality faced by firms experimenting with a new technology. The purpose of the paper is to analyze how herd behaviour is affected by this additional component and whether it can make less likely the failure of agents to adopt the most efficient technology.

We consider a stochastic public signal, that is, all firms receive the same signal about the economic environment. Intuitively, when firms decide about the adoption of a new technology they can look at the way in which consumers in another country have reacted to the previous introduction of the same technology. This would be a noisy signal because of different behaviours of their customers. Similarly, they can have some beliefs about government's policy, that is about public agencies' behaviours in supporting the new technology. Again this would be a noisy signal given that they are "blind".

Such a symmetric information structure makes sense: firms perceive the same information about the economic environment's preferences. This assumption turns out to be useful to find a threshold of the signal for the new technology to be adopted and, in general, for the technology choice to be independent of the other users.

2.2 Analytical framework

Consider the problem of a sequence of firms choosing between two competing technologies with unknown values. It is beneficial for firms to choose the technology that will be adopted by most other firms because of the presence of network externalities.

N risk-neutral firms choose between a "risky" new technology (B), and a "safe" old technology (A). They act in an exogenous sequence and the choice is irreversible. They receive an informative signal about the state of the world, represented by the economic environment. The signal y belongs to the continuous interval $[\underline{y}, \overline{y}]$, where a high level of the signal suggests a good state of the economic environment whereas a low level of the signal suggests a bad state of the economic environment. Firms' payoffs depend on the intrinsic value of the technology, on the network benefit, increasing in the number of people choosing the same technology, and on the economic environment (represented by a random variable indexed by θ) that could or not be favourable to a technological change or technological innovation. In particular, it is assumed there are two states of the world: θ can assume value either G, that is "good" for B (the economic environment as a whole is conducive to change), or $\overline{G}$, that is "bad" for B. Nature selects which state of the world occurs. The old technology (A) provides a low payoff that is independent of the state of the economic environment. The new technology (B) provides a potentially high payoff, but requires that the economic environment as a whole be conducive to change, in this case the firm adopting the new technology enjoys some additional payoff (s).

The net benefit for an individual choosing A is given by $\alpha + \nu_n$, when there are n firms choosing A, where ν_n is the positive network benefit increasing and concave in n (with $\nu_1 = 0$) and α is the intrinsic benefit of technology A.

The net benefit of choosing B is:

$$\beta + x = \begin{cases} \beta + \nu_n + s & \text{if } \theta = G \\ \beta + \nu_n & \text{if } \theta = \overline{G} \end{cases}$$

where β is the intrinsic benefit of technology B and where $x = \nu_n + s$ with $s > 0$ representing an additional benefit, if $\theta = G$ and n out of the N users choose technology B and $x = \nu_n$, if $\theta = \overline{G}$ and n out of the N users choose technology B. The intuition for s can be explained, referring to Adner (2003): supposing that both technologies guarantee the threshold level of performance required by consumers,[4] we argue that a positive demand environment can add a positive reward (for example in terms of sales), improving the final performance of the new technology. Alternatively, it can be interpreted as a subsidy in case the government chooses to support the technological innovation. A third interpretation is in terms of an increase in productivity: an economic environment that is conducive to change could lead firms to further improve the technology resulting in a higher intrinsic benefit, say, $\gamma = \beta + s > \beta$.

The final performance of the new technology is uncertain until the end of the game, because once B is chosen β becomes known but the final payoff depending on θ, doesn't. Firms receive a signal about the economic environment, update their beliefs and when deciding between the two alternative technologies, they take into account this potential "reward" from the economic environment.

Consider the timing of the model:

1. Nature selects which state of the world occurs.

2. Users have a uniform ignorance prior about the economic environment, θ. At the beginning of the period, they receive an informative signal about θ and so update their prior beliefs using Bayes' rule.

3. Users choose the technology sequentially and, once a technology is chosen, its true value is known.

4. The economic environment θ is revealed.

The case of symmetric information is similar to Choi (1997) since, indeed, there is no private information, and herd behaviour arises, as in his model, because of the informational externalities and the risk aversion. However, as

[4] That is, both technologies if adopted lead to a positive performance given by their intrinsic values, α and β, respectively

shown later, this assumption is sensible and the economic environment turns out to be an important element to take into account when deciding whether to change its own technology. This new source of uncertainty affects the experimenting bias, making the adoption condition more or less stringent under certain conditions.

2.3 The equilibrium decision rule

Suppose firms receive a public signal (y) about the state of the economic environment. When they have to choose, they observe the choices of their predecessors and the signal that is equal for all firms. In order to model the assumption that A represents the old and safe technology, suppose that all predecessors have chosen technology A, implying that its intrinsic value α is known.

Proceeding by backward induction, it is possible to get the equilibrium decision rule for each user in the queue. For convenience, all the computations are in the appendix.

Denoting $a_j(y)$ the action of firm j, depending on the signal y, it is shown that the formula for the k^{th} user to experiment with the new technology B is:

$$E(\beta) + sP[G|y, (a_j(y) = A)_{j<k}]$$
$$> \alpha + \nu_N - \nu_{N-k+1}P[(a_j(y) = B)_{j>k}|y, (a_j(y) = A)_{j<k}] \quad (1)$$

where $P[G|y, (a_j(y) = A)_{j<k}]$ is user k's posterior belief about the state of the economic environment, and $P[(a_j(y) = B)_{j>k}|y, (a_j(y) = A)_{j<k}]$ is the probability that, given the signal and given that all previous users have chosen technology A, all subsequent users choose B.[5] Condition (1) means that user k experiments with the new technology if and only if the posterior expected payoff of choosing B is bigger than that of choosing A.

Note that this inequality is harder to satisfy as k increases because, since the network benefit function ν_n is increasing in n, the RHS of (1) is increasing in k while the LHS does not change with k.[6] In words, starting from the last user, as we go back in the adoption queue, the incentive to experiment with the new technology increases because the potential network we could join is larger. For example, supposing all previous users have chosen A, user N experimenting with the new technology will not enjoy the network benefit

[5] In other words, it is the posterior probability that the final performance of technology B turns out to be better than that of technology A.

[6] Given the symmetric information structure, the posterior probabilities $P[G|y, (a_j(y) = A)_{j<k}]$ and $P[(a_j(y) = B)_{j>k}|y, (a_j(y) = A)_{j<k}]$ are identical for any k.

because she would be the only one adopting technology B and $\nu_1 = 0$. User $(N-1)$ experimenting with B would have the potential network benefit, $\nu_2 > 0$, user $(N-2)$ would enjoy ν_3 and so on, in the adoption queue.

Thus, the first result is that the second user turns out to be the pivotal one in the technology choice. Given that the first user has chosen technology A, the second user has the bigger incentive to experiment with the new technology, i.e., if she does not adopt it, it will never be experimented. Therefore, the condition for technology B to be adopted, is the corresponding condition for user 2, i.e., condition (1) computed in $k = 2$:

$$E(\beta) + sP[G|y, a_1(y) = A]$$
$$> \alpha + \nu_N - \nu_{N-1} P[(a_j(y) = B)_{j>2}|y, a_1(y) = A]$$

or, equivalently,

$$E(\beta) - \alpha > (\nu_N - \nu_{N-1}) - sP[G|y, a_1(y) = A]$$
$$+\nu_{N-1} P[(a_j(y) = A)_{j>2}|y, a_1(y) = A] \tag{2}$$

since $P[(a_j(y) = B)_{j>2}|y, a_1(y) = A] = 1 - P[(a_j(y) = A)_{j>2}|y, a_1(y) = A]$, where

$$P[(a_j(y) = A)_{j>2}|y, a_1(y) = A] =$$
$$P\left\{\beta + \nu_{N-1} P[\overline{G}|y, a_1(y) = A] + (\nu_{N-1} + s) P[G|y, a_1(y) = A] < \alpha + \nu_{N-1}\right\} =$$
$$P\left\{\beta < \alpha - sP[G|y, a_1(y) = A]\right\}.$$

Proposition 1 *Once the first user has chosen technology A (representing the old and safe technology), the new and risky technology (B) is adopted if and only if the second user experiments with it, or equivalently if and only condition (2) is satisfied.*

In other words, given that user 1 has chosen technology A, if condition (2) is satisfied, user 2 chooses technology B because it provides a higher expected payoff and it means that the new technology is experimented. The following users will choose between A and B depending on β, that now is revealed, and on their posterior beliefs about the economic environment. On the other hand, if condition (2) does not hold, condition (1) does not hold either, for all k, thus all users choose technology A since it provides a higher expected payoff. Hence, the new technology will never be experimented.

2.4 Comparison with Choi (1997)

This result is analogous to that found by Choi, without the presence of a public signal about the economic environment. In particular, let us state the corresponding condition for the adoption of the new technology in his model in order to compare these two cases. The condition found by Choi, is:

$$E(\beta) - \alpha > (\nu_N - \nu_{N-1}) + F(\alpha)\nu_{N-1} \tag{3}$$

where $F(\cdot)$ is the distribution function of the uncertain value of technology B, so that $F(\alpha)$ represents the probability that the new technology is not adopted, i.e., $P(\beta < \alpha)$, and it is increasing in its argument. Re-writing condition (2) in terms of the distribution function of β, $F(\cdot)$, it becomes:

$$\begin{aligned} E(\beta) - \alpha > (\nu_N - \nu_{N-1}) - sP[G|y, a_1(y) = A] \\ +F[\alpha - sP(G|y, a_1(y) = A)]\nu_{N-1} \end{aligned} \tag{4}$$

Now it is easy to compare the two results. First of all, note that the LHS of conditions (3) and (4) are the same, while the RHS of (4) is smaller than that of (3), since $F[\alpha - sP(G|y, a_1(y) = A)] \leq F(\alpha)$ and the new term, $-sP[G|y, a_1(y) = A]$, is nonpositive. Thus, condition (4) is in general less stringent than condition (3), or, in words, with this kind of uncertainty about the economic environment the new technology is more likely to be adopted. The strength of the latter depends on the level of the signal y. In particular, for certain values of y these two conditions are equal. The posterior belief about the economic environment, $P[G|y, a_1(y) = A]$, in (4), depends on the signal received by users, and if the signal y is low, suggesting a bad state of the world, the posterior belief on θ will be such that $\theta = \overline{G}$ with a high probability, i.e., $P[\overline{G}|y, a_1(y) = A]$ is decreasing in y or, equivalently, $P[G|y, a_1(y) = A]$ is increasing in y. In the limit, if the signal is low enough, this probability goes to zero, and so condition (4) tends to condition (3). Then, in a sense Choi's model can be read as a particular case of our model, in particular, the case of pessimistic posterior beliefs about the economic environment.

The result of a lower experimenting bias is explained by the fact that the potential additional benefit associated with the new technology, makes it less risky than in Choi. The fact that the bias against the adoption of a new technology decreases is an important result since this is in accordance with the empirical evidence that a less efficient technology is not likely to conquer the market and lock out a more efficient one (Liebowitz and Margolis, 1994).

Proceeding as in Choi's model, let us define the bias against experimenting with the new technology, as the difference:

$$E(\beta) - \alpha^* = (\nu_N - \nu_{N-1}) - sP[G|y, a_1(y) = A] + F[\alpha^* - sP(G|y, a_1(y) = A)]\nu_{N-1} \quad (5)$$

where α^* is the critical value of technology A at which user 2 is indifferent between the two technologies, and where the amount of distortion depends on s and y, given the intrinsic values of the two alternative technologies. Note that, for a given level of the signal, y, there exists a unique α^* satisfying (5), since the LHS is strictly decreasing in α^* and the RHS is strictly increasing in α^*.

Analysing the different terms of the RHS of this condition we can state that this bias depends on three terms. For the sake of comparison, we write Choi's bias as:

$$E(\beta) - \alpha^* = (\nu_N - \nu_{N-1}) + F(\alpha^*)\nu_{N-1} \quad (6)$$

Note that it is strictly positive because both terms of the RHS are strictly positive.

The first term in (5), the same as in Choi, is the so called *installed-base disadvantage for a new technology*, $(\nu_N - \nu_{N-1})$, that is the marginal network benefit due to the additional user joining the network: it goes to zero as N goes to infinity because of the concavity of ν_N. Therefore we can conclude that the second and the third terms are largely responsible for the bias. The third term is similar to the corresponding term in Choi, but it is smaller $(F[\alpha^* - sP(G|y, a_1(y) = A)] \leq F(\alpha^*))$: taking into account the possibility of a "good" state of the world it is more likely that the final performance of the new technology is bigger than α. The second term, the new one with respect to (6), can be interpreted as the hope of enjoying the subsidy.

These two last terms appear when we introduce uncertainty about θ and about the true value of the untested technology. Suppose there is uncertainty only about the true value of the untested technology as in Choi; then, as argued by the author, the adoption of B reveals information about it that will be incorporated in the subsequent users' adoption decisions. In this case the second term disappears and the third reduces to $F(\alpha^*)\nu_{N-1}$.[7] This term can be explained in terms of asymmetric risk associated with trying the new

[7]The assumption is that, without uncertainty about the economic environment, there is no potential subsidy.

technology B. If it succeeds, the second user gets the direct benefit of the better technology but no other incremental gain, since he will be part of a large network either by taking A or B. In contrast, if B does not succeed, the second user suffers the direct cost of the failure, plus the cost of being stranded without a network (which is guaranteed not to happen if he chooses A). However, introducing also the second source of uncertainty, the adoption of the new technology implies the possibility to enjoy the subsidy if θ is in favour of a technological change, possibility that is excluded in the case the user chooses technology A. This additional term makes the adoption of the new technology easier, because such a payoff structure makes the new technology less risky.

Next, Choi studies how the adoption bias changes changing the uncertainty about the value of the untested technology. Introducing a measure of the riskiness of the uncertain value of technology B, Choi's results, about the experimenting bias, still hold in our model, given that α does not enter in the new terms that appear in this extended version. In particular, assume that the distribution function $F(\beta;\sigma)$, where σ indexes the riskiness, satisfies the single-crossing-at-the-mean condition (SCM), i.e.,

Single-crossing-at-the-mean condition (SCM). The distribution functions of β corresponding to two different levels of riskiness, $\sigma^{'} > \sigma$, intersect only once at their mean, i.e., $F(\beta,\sigma) - F(\beta,\sigma^{'}) \geq (<)\ 0$, according to $\beta \geq (<)$ $E(\beta)$.

Then, the following results can be shown:

Proposition 2 *Let $\alpha^{*}(\sigma)$ be the critical value defined in (5) corresponding to the level of riskiness σ. Then, $\alpha^{*}(\sigma)$ is decreasing in σ, i.e., the experimentation bias is increasing with a mean-preserving spread in the distribution of the new technology.*

Proof See Choi (1997), pp. 415-416.□

This result, in turn, affects user 1's optimal decision, as follows:

Proposition 3 *The first user will adopt the less risky technology, A, over the more risky one, B.*

Proof See Choi (1997), p. 416.□

The intuition behind this result is that the first user prefers that her followers do not experiment with the other technology since she prefers to "enjoy" the network benefit. Thus, her decision will be biased against risky technologies, since her subsequent users have less incentive to experiment with them. Another result by Choi is that given two technologies with equal expected values, the first user will choose the less risky one. Further he shows that it is possible for an inferior technology in terms of expected value to be chosen by the first user for a sufficient level of riskiness. This result has important implications in terms of social welfare, since a more efficient technology could never be adopted.

2.5 Reversing the conclusion of the paper

The framework analysed so far allows us to improve the efficiency of the technology choice by decreasing the experimenting bias. By contrast, it is possible to consider a different payoff structure and to obtain the opposite result, i.e., a greater experimenting bias. We briefly analyse this alternative model.

Consider the following framework for the same technology problem: the net benefit for an individual choosing A is given by $\alpha + \nu_n$, when there are n firms choosing A; the net benefit of choosing B, when n out of the N users have chosen technology B, is:

$$\beta + x = \begin{cases} \beta + \nu_n & \text{if } \theta = G \\ \beta + \nu_n - c & \text{if } \theta = \overline{G} \end{cases}$$

where c represents the adjustment cost if $\theta = \overline{G}$. As before, the final performance of the new technology is uncertain until the end of the game, because once B is chosen β becomes known but the final payoff depending on θ, not yet. Firms receive a signal about the economic environment, update their beliefs and when deciding between the two alternative technologies, they take into account this potential cost.

In such a setting, proceeding as before, it is possible to show that it is the second user that has the greater incentive to experiment with the new technology. The condition for the adoption of technology B is, then:

$$E(\beta) - cP[\overline{G}|y, a_1(y) = A] + \nu_{N-1}P[(a_j(y) = B)_{j>2}|y, a_1(y) = A] > \alpha + \nu_N$$

where the probability that the subsequent users adopt the new technology is,

$$P[(a_j(y) = B)_{j>2}|y, a_1(y) = A] = 1 - P[\beta < \alpha + cP(\overline{G}|y, a_1(y) = A)]$$

Re-writing this condition in terms of the distribution function of β, $F(\cdot)$, it becomes:

$$E(\beta) - \alpha > (\nu_N - \nu_{N-1}) + cP[\overline{G}|y, a_1(y) = A] \\ +F[\alpha + cP(\overline{G}|y, a_1(y) = A)]\nu_{N-1} \tag{7}$$

To make a comparison, consider again Choi's condition (3). As expected, the result is opposite with respect to the finding of the previous setting. In fact, condition (7) is more stringent than (3), given that $F(\alpha) \leq F[\alpha + cP(\overline{G}|y, a_1(y) = A)]$ and the new term, $cP[\overline{G}|y, a_1(y) = A]$, is nonnegative. The potential cost the firm has to face in the "bad" state of the world makes the new technology more risky than before. Depending on the signal, that determines the posterior beliefs of the users, it is less likely for the new technology to be adopted. In particular, the posterior belief, $P[\overline{G}|y, a_1(y) = A)]$, is decreasing with the signal, thus, for a signal high enough this probability goes to zero and condition (7) reduces to (3). Again, condition (3) can be seen as a particular case of condition (7), that is the case of optimistic posterior beliefs about the economic environment.

The greater experimenting bias is explained by the fact that, in this setting, the informational externality arising from the adoption of technology B by user 2 is less strong than in Choi, and user 2 takes account of this fact: even if technology B is revealed better than technology A, i.e., $\beta > \alpha$, successive users do not adopt B with certainty because of the uncertainty about the adjustment costs in case of a "bad" state of the world. On the other hand, in Choi's setting, once the second user has chosen technology B, its value is known and firms can choose the best technology with certainty.

Accordingly, the bias against experimenting with the new technology becomes:

$$E(\beta) - \alpha^{**} = (\nu_N - \nu_{N-1}) + cP[\overline{G}|y, a_1(y) = A] \\ +F[\alpha^{**} + cP(\overline{G}|y, a_1(y) = A)]\nu_{N-1} \tag{8}$$

where α^{**} is the unique value of α that makes user 2 indifferent between the two alternative technologies, given that, fixed y, the LHS is strictly decreasing in α^{**} and the RHS is strictly increasing in α^{**}. With this payoff structure, the bias increases, in particular it is bigger than or equal to Choi's bias. Again it can be explained in terms of asymmetric risk associated with trying B. In fact, in such an opposite framework, the adoption of the new technology implies the possibility to face adjustment costs if $\theta = \overline{G}$, possibility that is excluded if the user chooses the old technology. This additional term makes the adoption of the new technology more difficult than in Choi: even once β is revealed greater than α, the second user could be stranded by the other users. The final result is that the underproduction of information, that takes place already in Choi, increases in this framework.

Finally, note that the further results obtained in propositions 2 and 3 still hold in this alternative setting. In fact, as before, we can see that α does not enter in the new terms of the experimenting bias. Therefore, again, following Choi's proofs, it is possible to show that $\alpha^{**}(\sigma)$ defined in (8) is decreasing in σ and that the first user will adopt the less risky technology A, over the more risky one, B.

2.6 "Trigger strategy"

Let us now draw away from Choi's analysis in order to study how the conditions for the adoption of the new technology vary with the signal. Following the terminology used by, among others, Dasgupta (2000) and Corsetti et al. (2000, 2001), it is assumed that an agent follows a trigger strategy if, under or over a particular level of the signal (the trigger), she chooses her action without looking at the other agents' actions. We wonder whether there exists a value of the signal that determines the technology choice independently of the other agents.

Let us concentrate on the first payoff structure that we call "incentive scheme", i.e., the net benefit of choosing the new technology B is:

$$\beta + x = \begin{cases} \beta + \nu_n + s & \text{if } \theta = G \\ \beta + \nu_n & \text{if } \theta = \overline{G} \end{cases}$$

with s representing an additional benefit interpreted, for example, as a potential subsidy by the government. It represents the most interesting case because, as shown before, it allows us to reduce the experimenting bias with respect to Choi. Consider how condition (4) varies with y to describe the optimal behaviour by users in terms of "trigger strategies". Condition (4) can be re-written as:

$$\begin{aligned} E(\beta) - \alpha + sP[G|y, a_1(y) = A] &> (\nu_N - \nu_{N-1}) \\ &+F[\alpha - sP(G|y, a_1(y) = A)]\nu_{N-1} \end{aligned} \tag{9}$$

Note that the LHS is increasing and continuous with the signal and the RHS is decreasing and continuous with the signal, so that there exists a unique value of y, say $\overline{y}^*$, such that, *ceteris paribus*, user 2 is indifferent between the two technologies. Thus, $\overline{y}^*$ represents the "trigger" for user 2 in the sense that for a signal higher than $\overline{y}^*$, she chooses the new technology. In paricular, as y decreases this condition reduces to Choi's condition because for a level of the signal low enough $P[G|y, a_1(y) = A)]$ goes to zero. On the other hand, if y increases this probability increases: in the limit, for a level of y high enough, say, $y \to \overline{y}$, $P[G|y, a_1(y) = A)]$ goes to 1 and (9) becomes:

$$E(\beta) - \alpha + s > (\nu_N - \nu_{N-1}) + F(\alpha - s)\nu_{N-1}.$$

If s is high enough, the RHS goes to zero and so surely condition (9) holds since the LHS is strictly positive, or equivalently, user 2 experiments with the new technology. Therefore, under certain conditions on y and s, it is possible to find an upper threshold for the signal, say $\overline{y}^*$, over which the new technology is always experimented.

By contrast, for the sake of completeness, consider the second payoff structure that we call "cost scheme", i.e., firms experimenting with the new technology face a potential cost in the "bad" state of the world. In this framework, as shown before, the condition for the adoption of the new technology is:

$$\begin{aligned} E(\beta) - \alpha - cP[\overline{G}|y, a_1(y) = A] &> (\nu_N - \nu_{N-1}) \\ &+ F[\alpha + cP(\overline{G}|y, a_1(y) = A)]\nu_{N-1} \end{aligned} \tag{10}$$

Looking at this condition we can see that the LHS is increasing and continuous in y, while the RHS is decreasing and continuous in y, so that there exists a unique value of y, say $\underline{y}^*$, such that, *ceteris paribus*, user 2 is indifferent between the two technologies. In particular, for decreasing values of y the LHS decreases while the RHS increases, in the limit when the signal is low enough, under certain conditions, (10) does not hold anymore. It is possible to find a lower threshold for the signal under which the new technology will never be adopted. Intuitively, if $y \leq \underline{y}^*$, where $\underline{y}^*$ represents the "trigger", the signal about the economic environment is so bad that the expected payoff from choosing the new technology is inferior to that of choosing A regardless of the actions of the rest of the firms and the value of technology B. For example, given that $y \in [\underline{y}, \overline{y}]$, suppose that if agents observe $y \to \underline{y}$, their posterior beliefs about θ is such that $P(\overline{G}|y, a_1(y) = A) \to 1$, and so the LHS goes to $E(\beta) - \alpha - c$. If the adjustment costs are high enough, the LHS is non-positive and so (10) does not hold since the RHS is strictly positive. The upper threshold is given by the level of the signal such that condition (10) converges to condition (3), that is, the level of y such that $P(\overline{G}|y, a_1(y) = A) \to 0$.

To sum up, such a framework offers a simple way to model an additional source of uncertainty that firms actually face in their innovation decisions. This uncertainty is represented, for example, by the role of the demand or by the role of the government. As shown, it is possible to induce firms, and in particular the second pivotal firm, to experiment or not with a new and risky technology by affecting the signal they receive and in turn their posterior beliefs, thus improving the economic performance in terms of social welfare.

3 Conclusions and extensions

The economic environment in which firms are, when deciding which technology to adopt, matters. Introducing, in two alternative ways, uncertainty about it, affects the technology choice. We have changed the information structure in Choi (1997) by introducing a noisy public signal observable and equal for each firm. The result is that the actual uncertainty about the economic environment changes the bias against the adoption of a new technology, while the reasons why users exhibit herd behaviour are the same as in Choi: informational externalities and risk aversion. Note that the possibility to make smaller the experimenting bias is important, because, in turn, it induces firms to experiment with the new technology. Therefore, once both technologies are experimented, the failure of agents to adopt the most efficient technology is less likely, or, in line with David's terminology, the number of "Angry Orphans" should decrease.

Since the basic framework of our model is similar to Choi, we share some limitations with him. In particular, it would be interesting to introduce an asymmetric valuation of the network benefit: the existence of users that are more or less independent of network externalities could mitigate the underproduction of information that takes place in the model.

The comments concerning this model, are the introduction of private information and endogenous timing in the adoption queue. Regarding the first issue, Dasgupta (2000) analyses herd behaviour with public and private information in the presence of strategic complementarities, but its payoff structure is extremely simplified with respect to Choi, since it requires a complete coordination in the players' actions in order to get the network benefit.[8] Considering the payoff structure of Choi in Dasgupta's model makes things very complicated in terms of expected payoffs since one needs to take account of all the possible combinations of actions of the successive users. In fact, since their actions depend on their own signal, they are potentially different from each other. In such a framework, it is impossible to compare

[8]This assumption about the network benefit being positive or zero is quite strange and economically difficult to justify, since in general it is continuous and increasing in the number of adopters of the same technology.

the conditions for the adoption of the different users in the queue, since it is impossible to compare posterior beliefs depending on private signals, and so to compare expected payoffs. The pivotal user, i.e., the user having the bigger incentive to experiment, could not be singled out anymore. Therefore, public rather than private information simpliflies the model and supposing that firms perceive the same information about the economic environment's preferences remains a sensible assumption.

Regarding the possibility to allow users to choose their time of entry, we refer to the second part of the model by Choi and to Dasgupta (2001). In Choi, endogenous timing increases the inefficiency because of a delay in the technology adoption. In our model, intuitively the result should go in the same direction, but with the possibility, again to reduce the inefficiency. On the other hand, Dasgupta (2001) develops a dynamic coordination game with social learning and costs to delay. He finds that "introducing a costly option to delay and learn can enable agents to sort themselves efficiently over time", the result is a more efficient outcome.

To conclude, our model considers uncertainty about the level of technology performance as well as uncertainty about the economic environment. The empirical evidence, indeed, suggests that consumers' and governments' preferences affect firms' incentives to innovate. Thus, our model provides a simple way to analyse the reality of an adoption technology problem characterized by network externalities. In particular, it allows us to fit better than Choi the empirical relevance, from both the point of view of the assumptions and the results. On the one hand, the final performance of the new technology is not revealed immediately with the adoption, in fact, uncertainty is resolved only some time after the technology choice. On the other hand, our set-up implies a reduction in the positive bias against a superior technology. Moreover, it makes it possible to induce firms to experiment with a new and risky technology by affecting the signal they receive and in turn their posterior beliefs, thus improving the economic performance in terms of social welfare.

4 Appendix

Consider the technology choice of the last user N, in particular suppose all the previous $(N-1)$ users have chosen A. Denoting $a_j(y)$ the action of firm j, depending on the signal y, the posterior expected value of B for user N is:

$$\begin{aligned} E_N[B|y,(a_j(y)=A)_{j<N}] &= E(\beta)+\nu_1 P[\overline{G}|y,(a_j(y)=A)_{j<N}] \\ &+ (\nu_1+s)P[G|y,(a_j(y)=A)_{j<N}] \\ &= E(\beta)+sP[G|y,(a_j(y)=A)_{j<N}] \end{aligned}$$

since $\nu_1 = 0$ by assumption, where $P[G|y,(a_j(y)=A)_{j<N}] = 1-P[\overline{G}|y,(a_j(y)=A)_{j<N}]$ is user N's posterior belief about the state of the economic environment.[9] On the other hand, the expected value of choosing A for user N is:

$$\alpha+\nu_N$$

Then user N chooses B, if and only if

$$E(\beta)+sP[G|y,(a_j(y)=A)_{j<N}] > \alpha+\nu_N \tag{11}$$

If this condition holds, user N chooses B and so the value of choosing A for user $(N-1)$ is $\alpha+\nu_{N-1}$, while if she tries B, her expected payoff is:

$$\begin{aligned} E_{N-1}[B|y,(a_j(y)=A)_{j<N-1}] &= E(\beta) \\ &+ sP[G,a_N(y)=A|y,(a_j(y)=A)_{j<N-1}] \\ &+ \nu_2 P[\overline{G},a_N(y)=B|y,(a_j(y)=A)_{j<N-1}] \\ &+ (\nu_2+s)P[G,a_N(y)=B|y,(a_j(y)=A)_{j<N-1}] \end{aligned}$$

$$= E(\beta)+\nu_2 P(a_N(y)=B|y,(a_j(y)=A)_{j<N-1})+sP(G|y,(a_j(y)=A)_{j<N-1})$$

given that

$$P[G,a_N(y)=B|y,(a_j(y)=A)_{j<N-1}]+P[\overline{G},a_N(y)=B|y,(a_j(y)=A)_{j<N-1})]$$
$$= P[a_N(y)=B|y,(a_j(y)=A)_{j<N-1}]$$

[9] Agents update their beliefs by Bayes' rule:

$$P(G|y,(a_j(y)=A)_{j<N}) = \frac{P(y,(a_j(y)=A)_{j<N}|G)P(G)}{P(y,(a_j(y)=A)_{j<N})}$$

.

and

$$P[\overline{G}, a_N(y) = B|y, (a_j(y) = A)_{j<N-1}] + P[\overline{G}, a_N(y) = A|y, (a_j(y) = A)_{j<N-1}]$$
$$= P[\overline{G}|y, (a_j(y) = A)_{j<N-1}]$$

So that user $(N-1)$ chooses technology B if and only if

$$E_{N-1}[B|y, (a_j(y) = A)_{j<N-1}] > \alpha + \nu_{N-1}.$$

The probability that user N chooses B, given the signal, is:

$$\begin{aligned} &P\{a_N(y) = B|y, (a_j(y) = A)_{j<N-1}\} \\ &= P\{\beta + \nu_2 + sP[G|y, (a_j(y) = A)_{j<N-1}] > \alpha + \nu_{N-1}\} \\ &= 1 - P\{\beta < \alpha + \nu_{N-1} - \nu_2 - sP[G|y, (a_j(y) = A)_{j<N-1}]\} \end{aligned}$$

since, once that user $(N-1)$ has tried B, β is known (but the state of the economic environment is still uncertain) and so user N will choose B if and only if

$$\begin{aligned} &\beta + \nu_2 + sP[G|y, (a_j(y) = A)_{j<N-1}] > \alpha + \nu_{N-1} \Leftrightarrow \\ &\beta > \alpha + \nu_{N-1} - \nu_2 - sP[G|y, (a_j(y) = A)_{j<N-1}] \end{aligned}$$

On the other hand, if condition (11) does not hold, user $(N-1)$ knows that if she does not try B, user N chooses A and so the value of choosing A for user $(N-1)$ is $\alpha + \nu_N$ and of choosing B is the same as before. Then, in this case, user $(N-1)$ chooses B if and only if:

$$E_{N-1}[B|y, (a_j(y) = A)_{j<N-1}] > \alpha + \nu_N$$

Combining the two cases analyzed, we can conclude that user $(N-1)$ will adopt B if and only if:

$$\begin{aligned} &E(\beta) + sP[G|y, (a_j(y) = A)_{j<N-1}] \\ &> \alpha + \nu_N - \nu_2 P[a_N(y) = B|y, (a_j(y) = A)_{j<N-1}] \end{aligned} \tag{12}$$

where $P[G|y, (a_j(y) = A)_{j<N-1}]$ is the posterior belief of user $(N-1)$ about the economic environment. Since condition (12) is less stringent than that for user N, (11), user $(N-1)$ has a bigger incentive to experiment with the

alternative technology.[10] Intuitively, user $(N-1)$ choosing B could join a larger potential network, while user N choosing B would be the only adopter of the new technology.

Next, analyze the decision problem of user $(N-2)$. If she chooses B, β is revealed and users $(N-1)$ and N will choose B if and only if

$$\beta+\nu_3 P[(a_j(y)=B)_{j>N-2}|y,(a_j(y)=A)_{j<N-2}]+sP[G|y,(a_j(y)=A)_{j<N-2}]$$
$$>\alpha+\nu_{N-1}$$

since, once β is known, given the public signal, both users do the same thing. Her posterior expected payoff of choosing B is

$$\begin{aligned}
E_{N-2}[B|y,(a_j(y) &= A)_{j<N-2}] = E(\beta)\\
&+ sP[G,(a_j(y)=A)_{j>N-2}|y,(a_j(y)=A)_{j<N-2}]\\
&+ (\nu_3+s)P[G,(a_j(y)=B)_{j>N-2}|y,(a_j(y)=A)_{j<N-2}]\\
&+ \nu_3 P[\overline{G},(a_j(y)=B)_{j>N-2}|y,(a_j(y)=A)_{j<N-2}]
\end{aligned}$$

$$= E(\beta)+\nu_3 P[(a_j(y)=B)_{j>N-2}|y,(a_j(y)=A)_{j<N-2}]$$
$$+sP[G|y,(a_j(y)=A)_{j<N-2}]$$

If condition (12) holds, at least user $(N-1)$ or at most both users $(N-1)$ and N choose B, and the value of choosing A for user $(N-2)$ is $\alpha+\nu_{N-1}$ or $\alpha+\nu_{N-2}$ respectively. Therefore, the condition for her to choose B is:

$$E_{N-2}[B|y,(a_j(y)=A)_{j<N-2}]>\alpha+\nu_{N-2}.$$ [11]

On the other hand, if condition (12) does not hold, user $(N-2)$ knows that if she does not try the new technology B, user $(N-1)$ chooses A as well as user N and so the value of choosing A for user $(N-2)$ is

$$\alpha+\nu_N$$

while if she tries B her expected payoff is the same as before. Then, in this case, user $(N-2)$ chooses B if and only if:

$$E_{N-2}[B|y,(a_j(y)=A)_{j<N-2}]>\alpha+\nu_N$$

[10] Note that, because of the symmetric information among firms, it can be assumed that they have the same posterior beliefs about the economic environment, given that all previous users have chosen A. In fact, starting with equal prior beliefs and receiving the same information about θ they update their beliefs in the same way.

[11] Note that, given $\alpha+\nu_{N-1}>\alpha+\nu_{N-2}$, for user $(N-2)$ to experiment with B, her expected payoff must at least be higher than $\alpha+\nu_{N-2}$.

Again, combining the two cases, we can conclude that user $(N-2)$ will adopt B if and only if:

$$E(\beta) + sP[G|y, (a_j(y) = A)_{j<N-2}] >$$

$$\alpha + \nu_N - \nu_3 P[(a_j(y) = B)_{j>N-2}|y, (a_j(y) = A)_{j<N-2}] \tag{13}$$

In general, the formula for the k^{th} user to try B is

$$E(\beta) + sP[G|y, (a_j(y) = A)_{j<k}] >$$

$$\alpha + \nu_N - \nu_{N-k+1} P[(a_j(y) = B)_{j>k}|y, (a_j(y) = A)_{j<k}]. \tag{14}$$

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