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Impact of Open Innovation on Industries and Firms – A Dynamic Complex Systems View

Abstract

This paper develops novel behavioural models of open innovation (OI) for competitive markets and uses them to compare the impact of two types of OI frameworks – open source (OS) and patent-licensing (PL). The dynamic consequences of OI, for both OS and PL, are studied using a complex adaptive systems approach. We examine how profits, technology levels, R&D investment, technology adoption and market structure evolve under each and are impacted by underlying market characteristics. While both OS and PL are found to be equivalent in technology outcomes, OS comes with additional advantages to participating firms. Firms in the OS framework earn higher profit and are more efficient with their R&D investments. The industry is less concentrated under OS than under PL, except when market size is very large. In both frameworks, consumer preference for new product adoption has a significant impact. When consumers adopt newly introduced products relatively quickly, market concentration is the higher and overall rate of technological progress slower. These results contribute towards a deeper theoretical understanding of OI, opening new avenues for future research.

Keywords: open innovation, open source, patent licensing, complexity, agent based model

1. Introduction

Open innovation (OI) as an innovation paradigm is increasingly being discussed and debated, with regard to national innovation systems (Chesbrough, 2017; Wang et al., 2012). Chesbrough (2003a) defines OI is a paradigm where firms "can and should use external ideas as well as internal ideas, and internal and external paths to market", in their effort to innovate new products and technologies for the market place. In response to the growing literature on the topic, the definition has been further generalised to "a distributed innovation process based on purposively managed knowledge flows across organizational boundaries, using pecuniary and non-pecuniary mechanisms in line with the organization's business model" (Chesbrough and Bogers, 2014).

Open innovation helps firms to improve their innovation performance by helping them to access new ideas and knowledge outside their boundaries and to reduce the costs of R&D investment and share risks (Leckel et al., 2020; Elia et al., 2020). Open innovation as a phenomenon is not only economically efficient but also increases the likelihood of breakthrough innovations, resulting in a higher likelihood of business growth and business development (Natalicchio et al., 2014; Radziwon and Bogers, 2019). New technological breakthroughs in the sphere of digitization and digital transformation across sectors of energy, health, transportation, finance etc. have radically altered the way innovation is carried out, and have highlighted the importance of collaboration and co-creation in knowledge markets (Bogers et al., 2018; Cassiman and Valentini, 2016).

The idea that the innovation process can be a collaborative effort, even among competing firms, underpins the concept of OI and has resulted in a growing interest in its benefits, costs, types, underlying processes and mechanisms, and suitability (Nestle et al., 2019; Lee et al., 2020). While several empirical studies have examined how OI is adopted by innovating firms, the theoretical literature on this topic is limited (Dahlander and Gann, 2010; West et al., 2014). Two questions, in particular, need addressing.

First, given that OI can take various forms, each characterised by varying degrees of openness, the benefits and costs of openness remain largely unexplored, including what constitutes an optimum degree for an industry and a firm (Cassiman and Valentini, 2016). In particular, under what circumstances should firms *choose* a completely open framework – such as the *open source* approach – as opposed to the more traditional market-led *patent-licensing* framework which protects and monetizes knowledge? While the OI paradigm does not preclude firms from adopting either framework, firm and industry level incentives for choosing one over another are unclear (Freel and Robson, 2017; West et al., 2014; **?**).

Second, the actual process by which firms "source" external knowledge and the decision processes underpinning this needs further research (Cassiman and Valentini, 2016; Laursen and Salter, 2014; Scuotto et al., 2020). In particular, OI is essentially a complex interactive process whereby innovating firms may extract knowledge from the external environment, contribute back to the environment with new knowledge and thus form implicit linkages with various actors within the ecosystem. However, very little is known about the potential dynamic consequences of the choices these firms make. How does the ecosystem evolve and does the adoption of a particular kind of OI framework confer specific advantages to the system as a whole?

This paper addresses these questions by studying the long term impact of adopting two alternative varieties of OI – the *open source* (OS) framework versus the *patent-licensing* (PL) one, and exploring the long term consequences of such choices. Within the OS framework, firms do not impose any form of "protection" on the intellectual property they generate and hence can freely access each others' knowledge and technology. On the other hand, firms adopting the PL framework are legally required to purchase a license in exchange for a fee, if they want to access each others' proprietary knowledge and technology. Comparisons are made based on firm-level outcomes such as performance and technology trajectory, as well as industry-level outcomes such as eventual market structure and concentration, overall technological outcomes and R&D efficiency. The micro-foundations of firm behaviour within an OI paradigm are built using an adaptive mathematical model where firms are allowed to interact and exchange “knowledge" underpinning their innovations, and where these firms are allowed to “learn" from their past mistakes. Unlike previous theoretical representations of OI phenomena, our model combines micro and macro-level analysis of inbound and outbound OI and therefore it provides a richer interpretation of the impact of OI practices on technology development, and at the same time, exploring the impact of alternative OI practices on the evolution of the firm and the industry. Thus, this paper goes to the heart of what it means to be “open" within the OI paradigm, and how firms choose to innovate under different innovation environments.

Our analysis shows that an industry practising OI by implementing the OS framework confers specific strategic advantages to its firms over the one which implements the PL framework. These advantages arise despite having to sacrifice appropriation of short term benefits of innovating. These advantages are in terms of long term firm profitability, the efficiency of the innovation process and in terms of survivability of smaller firms. The latter is especially true for markets which are restricted in size (hence placing a limit on profitability), where we find that an OS framework results in a more equitable distribution of the market shares, making it easier for smaller firms to compete. Interestingly, no difference between OS and PL could be detected for aggregate technology outcomes for the industry. Finally, we are also able to show that *ceteris paribus*, the dynamic and long term impact of underlying industry and market-level characteristics on the evolving technology trajectory and market structure is highly significant but qualitatively similar for both OS and PL. Both number of competitors and the size of the market play a key role in determining the direction and nature of technology growth within either of the OI frameworks.

2. Background

Open Innovation as a concept took off in the academic literature following the seminal articles by Chesbrough (2006, 2003a,b). However, as revealed in studies such as Christensen et al. (2005) and Dahlander and Gann (2010), roots of openness in the innovation process is not a new phenomenon but has been present in varying degrees in many industries over several decades[1]. It has been

[1]While the IT technology, in particular, the software industry is often hailed as the pioneers of the OI paradigm through the open-source movement, notable examples can be seen elsewhere as well. For instance, well-known manufacturers such as Lego, GE, Coca Cola, P&G have used collaborative principles in generating new ideas for products. Examples of collaborations between direct and indirect competitors exist as well, such as the Open Innovation Network involving IT companies, between Microsoft and the Linux community, and the Structural Genomics Consortium

argued that innovation in firms has never in fact been an exclusively closed process, and its success required the free flow of ideas, knowledge and newly developed technologies between organizations (Chesbrough, 2003a). Nevertheless, a formal definition of OI implies that firms not only look externally in sourcing and acquiring new ideas and technologies (*inbound* innovation) but also explore options of revealing the results of innovation externally (*outbound* innovation) (Dahlander and Gann, 2010; Huizingh, 2011).

Inbound open innovation refers to the use of external knowledge to facilitate the internal innovation activities and it is usually done by building relationships and collaboration with external partners to access their technical knowledge. Outbound open innovation focuses on the external relationships companies build to facilitate commercialization. Dahlander and Gann (2010) further classify each of these activities based on whether these involve pecuniary versus non-pecuniary processes. From a value perspective, the possible combinations between the inbound-outbound dimensions and the related pecuniary and non-pecuniary characteristics have been identified to clarify how the OI activities can generate value the firm can appropriate (Pustovrh et al., 2020; Radziwon and Bogers, 2019).

OI as a concept comes in many forms and hence, firms can adopt many alternative innovation strategies which can be classified as open (Chesbrough, 2017; Huizingh, 2011). Collaboration in innovation can happen between firms engaged in a vertical relationship such as that of between suppliers and customers (Gassmann et al., 2010; Hagedoorn and Duysters, 2002; Hagedoorn, 1993), between public and private enterprises (Fogenberg and Thorpenberg, 2012), and finally between competitors within the same industry and/or market (Han et al., 2012). OI collaborations, in general, are long term arrangements, and, likely, new knowledge generated as a result of such arrangements and its sharing rules would have consequences for both collaborations and competition in the future.

Inherently, an OI system can be compared to a heterogeneous innovation ecosystem which is usually made of different types of economic agents whose activities are aligned so that they can extract value through their collective efforts (Adner, 2006). Importantly these ecosystems are characterised by internal dynamics which can lead to different evolutionary paths given different alternative configurations of agents and their interconnections (Mei et al., 2019; Sant et al., 2020). Previous research has mostly focused on the perspective of one firm interacting with external partners, with little attention on the system as a whole. Only recently, has the literature started to examine the relationship between OI practices, networks and geographically bounded systems, emphasizing on the relationship between practice and evolution of the system. Several authors find that the

involving Biotechnology and Pharmaceutical companies.

dynamics of OI varies across different ecosystems, and in reality, the attitude of firms towards OI is a result of a combination of the different elements within the ecosystem itself (Lyu et al., 2019; Radziwon and Bogers, 2019). The importance of path-dependency is highlighted in these studies (Lecocq and Looy, 2016; Mei et al., 2019) as the initial choices in terms of OI practices influences the dynamic evolution of the system eventually conditioning the choices of all the firms involved in the system.

Recent literature has examined the relationship between network characteristics and OI. For instance, researchers have focused on other characteristics of the networks such as network embeddedness (Echols and Tsai, 2005), network structure (Garriga et al., 2013), and network ties (Westergren and Holmström, 2012). It has been shown that network embeddedness, which reflects the specific extent of a firm's inter-relationships with others in an innovation network (Echols and Tsai, 2005), is one of the most crucial factors determining outcomes of practising OI (Chesbrough, 2006; Koka and Prescott, 2008).

While the importance of external knowledge search and efficient knowledge recombination has been emphasised by several authors when discussing OI (Chesbrough and Bogers, 2014; Mina et al., 2014), different practices of OI come with different challenges. As recent research has highlighted, imitation risks may influence the performance of the innovation process when firms opt for the most revealing OI practices (Veer et al., 2016). Additionally, Zobel (2016) and Veer et al. (2016) highlight the importance of understanding how choices of the appropriability mechanisms can influence the OI patterns. In this respect, the interface between appropriability strategies across organizational boundaries and OI is an important area to study, as it affects the way firms innovate while cooperating with external partners.

Discussion about OI cannot ignore the *dynamic* processes underlying within the innovation ecosystem. However, these dynamic processes are only beginning to be explored through empirical studies using longitudinal data. For instance, in a very interesting empirical analysis of the computer components industry, Henkel et al. (2014) explore the antecedents and evolution of "openness" amongst firms which traditionally followed a more closed model. They found that both the changing external environment (such as the increased prevalence of OS in complementary industries), coupled with shifting nature of consumers' demand led to firms learning of the benefits of engaging in OI. Love et al. (2014) examine the process through which firms and managers dynamically *learn* about beneficial external linkages and knowledge sources for innovation and new product development and the learning process has a key role in determining future innovation performance. Although these studies focus on how and why OI emerge among firms, an exploration of the consequences of opening up the innovation process and the micro-mechanisms underpinning it, is yet to be definitively understood.

2.1. Contribution

The model presented here focusses on the benefits and costs of OI implemented through two alternative pathways of OI - the OS and PL frameworks. A comparative exploration of the consequences of varying degrees of openness on the firm and industry outcomes is an under-researched area in innovation studies (Freel and Robson, 2017). The way to address this gap is by allowing both inbound and outbound innovation within an industry, for the alternative frameworks. Firms in our model can source knowledge externally (from competitors), and in turn, make available the fruits of their research to competitors (freely in OS and through costly licensing in PL). Such a model incorporates both the collaborative and competitive aspects of a typical OI consortium comprised of firms with similar interests and objectives. The extant literature amply demonstrates the presence and importance of knowledge sharing among innovating firms, even if firms are involved in otherwise competitive relationships (Spencer, 2003; van Wijk et al., 2008; Hagedoorn and Wang, 2012).

The incentives to engage in open innovation have been explored theoretically by Gambardella and Panico (2014) in case of asymmetric firms, examining the incentives of a firm with stronger bargaining power to collaborate with another with weaker bargaining power. While our model examines incentives towards openness in innovation as well, the approach is different in two ways. First, we examine incentives in terms of long term profitability, where the benefit of access to superior technology in the future needs to balanced with the cost of higher returns from closed innovation in the present. The choice is between appropriating the benefits of innovations in the present versus being able to costlessly access superior technology from rivals in the future and examining under what market conditions one is preferred over the other.

Second, we examine how such choices are dependent on underlying market conditions. The role of the market and the consumer in the innovation process itself is important, particularly through the involvement of users directly into the innovation process (Dahlander and Piezunka, 2014; von Hippel, 2005, 1998; Franke and Piller, 2003). While the concept of *direct* user involvement through customization or other means is beyond the scope of the model presented here, nevertheless, we allow *indirect* involvement through the incorporation of preferences towards new technologies and products within the behavioural model of the consumer. We show that for both OS and PL frameworks, market characteristics, in fact, have a significant impact on the technology outcomes and the shape of the technology trajectory, and hence should be appropriately considered by firms in their choice of innovation strategy.

Third, we address these questions using the *complex adaptive systems* approach (Arranz and Fdez de Arroyabe, 2009; Phillips and Linstone, 2016). This approach is particularly suitable for modelling innovation systems with multiple actors, given the highly interlinked and adaptive search-driven behaviour of these actors (Fleming and Sorenson, 2001; Phillips, 2008; Sorenson et al., 2006). First, an analytical model sets the micro-foundations of firm behaviour within a static setting, and this acts as a benchmark for the dynamic analysis. The latter is carried out using an Agent-Based Modelling (ABM) methodology. ABM is particularly suitable for dynamic systems which are deemed to be "complex", that usually signifies a large number of heterogeneous participants with inter-linkages between them, giving rise to various types of "emergent" behaviour[2]. While innovation studies in general have witnessed a steady rise in the use of ABM[3], it is particularly suitable for modelling OI, given that knowledge-based interactions between firms set up implicit directed links, as a result of which macro-level outcomes are not predictable from micro-level behaviours.

The results have implications for overall innovation policy at the industry level and firms, to the extent of helping to decide between OI and PL routes of OI. The behavioural micro-foundations presented here are strategic in nature, examining the long term consequences of adopting an open innovation framework on the industry and participating firms. Hence, the models should not be used for short term innovation management at the firm level. We now present the mathematical foundations of the models in detail.

3. Models of Open Innovation and Behaviour

We consider a situation where N firms are competing against each other in a market with M consumers. At any given time t, the product developed by firm $i \in N$, embodies within it a technology level $x_i(t)$, and this knowledge can be improved through investments in R&D. These firms operate within an OI framework, implying that these technologies are not incompatible between the firms, i.e. one firm can adopt the technology of another for its own product and improve it through additional investments in research. We also assume that $x_i(t)$ is an ordinal measure of technology level, that is higher values of $x_i(t)$ imply more advanced technology which can be potentially more attractive to consumers[4]. Moreover, each firm $i \in N$ is endowed with some initial knowledge or starting technology $x_i(0)$ at $t = 0$.

[2]Emergence is said to occur when heterogeneity and interlinkages result in non-linear interactions between various components of the model, which give rise to a separation between micro, meso and macro properties in a system. The system as a whole (or the macro level) can exhibit surprising, unpredictable dynamic properties, which are usually not apparent at the level of individuals (micro). See Tesfatsion (2006) for a broader perspective.

[3]See for instance Garcia (2005), Ma and Nakamori (2005), Dawid (2006), Malerba et al. (2008) and more recently, Harper (2015).

[4]We do not distinguish between the underlying technology embodied in a product and the resulting characteristic(s). For instance, mobile phone manufacturers may use a high end processor (the technology) to improve speed (characteristic) and/or high density screen (technology) to enhance display (characteristic). Consumers may or may not be aware of the technology but is usually expected to be aware of the characteristics. Our model combines these aspects into one observable variable, $x_i(t)$ for tractability.

All consumers can observe the level of technology in the products. Their preferences are based on the level of technology and prices. The combined preferences of all consumers give rise to a market level demand for each product i at time t, and can be represented as,

$$D_i(t) = D_i(x_i(t), p_i(t), \mathbf{x}_{-i}(t), \mathbf{p}_{-i}(t))$$

where $p_i(t)$ is the market price charged by firm i for its product, and $\mathbf{x}_{-i}(t), \mathbf{p}_{-i}(t)$ represent the technology and price vectors respectively of all firms $j \neq i \in N$.

3.1. The Innovation Model

Firms are able to improve the current *stock* of technology embodied in their product only through further investments in R&D. For any firm i, this process is represented by,

$$x_i(t) = \tilde{x}_i + T\left(R_i(t), \epsilon_i(t)\right) \tag{1}$$

where, $\tilde{x}_i$ is the knowledge base of i being used to develop a new innovation. This is done using $T(\cdot)$, the *technology production function*, where $R_i(t)$ is the R&D investment made by i in t and $\epsilon_i(t) \in (0, \bar{\epsilon})$, is the stochastic component of investment in research, drawn from any given distribution $F(\epsilon)$, identical for all firms[5]. Naturally, $\dfrac{\partial T}{\partial R_i} \geq 0$ and $\dfrac{\partial T}{\partial \epsilon_i} \geq 0$, implying that technology is non-decreasing in investment and external technology shocks.

In practise, the base technology $\tilde{x}_i$ in (1) can represent either own technology developed by i or it could be a rival's technology adopted through OI. Both these cases can be represented as,

$$\tilde{x}_i = \begin{cases} x_i(t-1), & \text{if } i \text{ uses own technology stock} \\ x_j(t-1), & \text{if } i \text{ uses } j\text{'s technology stock, } j \neq i. \end{cases} \tag{2}$$

The firm's profit in period t, in the absence of any other lateral transfers, is represented as,

$$\pi_i(t) = p_i(t) D_i(\mathbf{x}(t), \mathbf{p}(t) \mid \mathbf{x}(t-1)) - R_i(t) - c.x_i(t) \tag{3}$$

where the profit is a function of price and actual demand for i's product minus the investment made in R&D, the cost of technology production c[6]. $\mathbf{x}(t)$ and $\mathbf{p}(t)$ are the vector of $x_j(t)$ and $p_j(t)$ for all $j \in N$. Note that given (2), demand for i's product is now conditioned on past technology profiles of all firms $\mathbf{x}(t-1)$).

[5]This represents the uncertainty in the outcome of research in every area of science and technology. Higher levels of investment in R&D make improvements in technology more likely, but not certain.

[6]This imbibes the idea that products with more advanced technology cost more to produce. Process innovations may actually reduce manufacturing cost, but in this paper, we focus on product innovation only. We also ignore economies of scale or economies of technology which can reduce costs in the long run. Our assumption of increasing costs of production of technologically superior products is certainly true in most cases when a new product has just been introduced in the market.

The following assumptions regarding the market and the information available to firms underpin the innovation model presented above.

Assumption 1. *The number of firms in the market is fixed exogenously, and no entry or exit is allowed.*

Assumption 2. *At any given period t, each firm i is able to observe firm j's technology technology $x_j(t-1)$ and price $p_j(t-1)$ from the previous period.*

Assumption 3. *Firms learn from past mistakes when choosing strategies using a reinforcement learning mechanism based on profitability.*

In this dynamic model of innovation, each firm i makes two choices every period t. First, it decides where to source the base technology from, i.e. internally or externally. Second, it decides on the level of investment in R&D and price of the final product it sells in the market. All firms N undertake these decisions *simultaneously* in t, i.e. without knowledge of what other firms are deciding in the same period, but with full knowledge of available technologies from $t-1$.

To focus exclusively on the impact of OI and to reduce unnecessary complications, we make a firm's choice of $R_i(t)$ and $p_i(t)$ deterministic, and that of $x(t)$ strategic, in our model. Thus, the choice of $R_i(t)$ and $p_i(t)$ is given by the following rules:

$$R_i^*(t) = \begin{cases} R_{min} + \alpha\pi_i(t-1), & \text{if } (\pi_i(t-1) - \pi_i(t-2) > 0 \\ R_{min}, & \text{otherwise} \end{cases} \tag{4}$$

and,

$$p_i^*(t) = \text{avg}\{c.x_i(t), \min p_{-i}(t-1)\}. \tag{5}$$

The mathematical rule expressed in (4) simply states the following. In every period an innovating firm will invest a minimum amount (R_{min}) towards research. However, if profits have *increased* in the preceding period, then an additional proportion α of profits from last period is added to the minimum investment, implying that increased profitability increases investments in R&D[7]. And the rule in (5) states that, prices are an average of the cost of technology and the minimum price of competitors in the last period – implying that while more technologically superior products cost more and hence has an upward influence on price, competition results in a downward influence on price at the same time.

Since the choice of the base technology is a strategic choice in the model, we define a strategy set $S = \{s^1, \ldots, s^K\}$ consisting of K independent choices available for a firm. What these independent

[7] This assumption of the positive impact of profit on R&D is evidence driven. See for instance, Brown et.al. (2012) and Brown et.al.(2013).

choices actually are depends on the type of OI framework under consideration (between OS and PL), and we shall define them shortly. Let $\Sigma_i = \{\sigma^1, \ldots, \sigma^K\}$ be a probability density function defined over S for firm i, such that σ^k is the probability with which i chooses strategy $s^k \in S$.

In every period t, each firm i randomly chooses a strategy from S using the distribution $\Sigma_i(t)$. We allow the firms to *learn* and *adapt* over time, using a simple *reinforcement algorithm*[8]. Correctly chosen strategies (leading to an increase in profits) are rewarded by a fixed increment $0 < \lambda < 1$ in the corresponding probability for the next period, and incorrectly chosen strategies (leading to decrease in profits) are penalized by the same amount. This learning rule can be expressed as:

$$\text{If } \pi_i(t) \geq \pi_i(t-1) \Rightarrow \begin{cases} \sigma_i^k(t+1) = \sigma_i^k(t) + \lambda \\ \sigma_i^{-k}(t+1) = \sigma_i^{-k}(t) - \dfrac{\lambda}{K-1} \end{cases}$$
$$\text{If } \pi_i(t) < \pi_i(t-1) \Rightarrow \begin{cases} \sigma_i^k(t+1) = \sigma_i^k(t) - \lambda \\ \sigma_i^{-k}(t+1) = \sigma_i^{-k}(t) + \dfrac{\lambda}{K-1} \end{cases} \tag{6}$$

The above describes an evolutionary model of innovation, where firms simultaneously choose the *source* of the base technology strategically, given the rules set by the underlying OI framework, OS or OL. Each endows firms with specific set of available strategies, which we now describe.

3.2. Nature of open innovation - OS and PL

Depending on the OI framework being considered, the strategic choices available to firms may be different.

The OS model is based on the premise that all firms are part of a consortium where any new knowledge created by the members is commonly owned. This implies that the members of the consortium are able to access each others' technology and incorporate them into their products *free of cost*[9]. New technologies developed through research is shared among the members and all members are able to incorporate it within their own products, *at a lag of one period.* At time t, firm i has two choices – use internally developed technology or adopt external (current market leader's)

[8]The fact that firms experiment, make mistakes and learn from them has been explored previously, including use in agent based models. See for instance, Aldrich and Yang (2013); Argote and Miron-Spektor (2011); Sengupta and Greetham (2010).

[9]We are examining an OS framework where the members of the consortium are all competitors in the market place. However, they are willing to co-create and share knowledge amongst themselves, which gets embodied in products they sell in the market. This does not imply that these products are not differentiated which occurs as firms improve on shared know-how by investing in further research. Additionally, we are not modelling the *process* of consortium formation, but the *implications* of one. Modelling the process itself, or how the consortium came into existence is beyond the scope of the present model.

technology as $x(t-1)$. Therefore for OS, $S = \{s^1, s^2\}$, where s^1 is the strategy representing use of external (in this case, the current market leader's) knowledge and s^2 is the strategy representing the use of internal knowledge.

The PL model assumes a framework of intellectual property protection to be in place within the industry. This implies that all new technologies being created by a firm is protected through patents. There is no consortium of firms any more, but the knowledge about each others' technology is freely available due to *disclosure requirements*[10]. A firm wishing to adopt another's technology as the base will now have to apply for a license in lieu of a licensing fee, or costlessly copy a rival's technology at the risk of being caught and penalized with a fine. We assume two simplifying features of PL framework – first, all license applications are granted and second, the licensing fee takes the form of a royalty, which is a per unit amount paid by the licensee to the owner of the patent for every unit his product sold in the market. We also assume that patents and licensing agreements are valid for one period only[11].

If firm i licenses firm j's technology in period t, then i pays j a fee $rD_i(t)$, where r is an exogenously fixed royalty per unit of output sold. Alternatively, firm i can also choose to *infringe* the patent and copy j's technology directly without paying the licensing fee. This carries the possibility of getting caught with probability Φ, which is also exogenously fixed. If caught, the infringing firm pays a fine proportional to the level of infringement, $\rho|x_i(t-1) - x_j(t-1)|$, where $\rho > 0$ is exogenous as well. In effect, r, Φ, ρ are parameters of the PL model, and their values indicate the strength of the patenting system. In comparison, OI is a limiting case of the PL model where $r = \Phi = \rho = 0$. Hence, lowering any of these parameters in PL is essentially weakening of the patenting system and hence, a move towards OI.

The above implies that for PL, the strategies available to a firm are $S = \{s^1, s^2, s^3\}$, where s^1 represents the use of the licensing strategy, s^2 represents infringement and s^3 represents the use of in house knowledge. In this model, licensing and infringement of technology is once again, borrowing the current market leader's technology.

In both OI and PL, all firms in the market simultaneously play a dynamic multi-period game, where the period t game from the point of view of i can be described by:

1. Firm i observes $x_j(t-1)$ and $p_j(t-1)$ for all $j \in N$.

[10] Patenting jurisdictions generally require a full disclosure of the technology being patented. This makes the knowledge about the technology freely available but the technology itself is protected against duplication through the patent.

[11] This is a simplifying assumption imposed in order to keep the model tractable. Licensing agreements across multiple time periods introduces the possibility of other strategic considerations for firms, which are currently outside this model's scope.

2. Firm i chooses $x(t-1)$ based on the strategy profile S and the probability distribution $\Sigma_i(t)$.

3. Firm i decides on $R_i(t)$ and $p_i(t)$ based on 4 and 5, realizes $\epsilon_i(t)$, creates a new technology and product, sells the product in the market, and earns profit $\pi_i(t)$ net of any fees or fines.

3.3. The Market

Consumers in our model act as independent non-strategic agents, who have the option of choosing from any one product among the N choices available every period. Simply put, each consumer will independently choose one which appears *subjectively*, to be the best choice. However, they will only make a purchase if there exists a product which is technologically superior to the one they currently possess (purchased in an earlier period) and is feasible within his own budget. They will continue to “use" this product till a new purchase is made in some future period. As we see below, a consumer need not purchase a product in every period, but may go through several periods without purchasing anything new.

Each consumer $m \in M$ is endowed with $(x_m, p_m) \in R^2$, which represents the *minimum* technology level they want and the *maximum* willingness to pay respectively. This allows us to define a *consideration set* for consumer m, defined as

$$C_m(t) = \{j \in N : x_j(t) \geq x_m, p_j(t) \leq p_m\} \tag{7}$$

which is the set of potential products, consumer m would choose from. Note that it is possible that $C_m(t)$ is empty (ϕ) in any given t, in which case they do not purchase any product in period t. If $C_m(t)$ is non-empty, consumer m evaluates all alternatives $j \in C_m(t)$ using the agent specific utility function,

$$U_m^j(t) = \beta_m x_j(t) - (1 - \beta_m)p_j(t) \tag{8}$$

where, $0 \leq \beta_m \leq 1$ is the weight placed by m on product technology and $(1 - \beta_m)$ is the residual weight on price.

If the best product in $C_m(t)$ has a utility sufficiently higher in percentage terms than the utility of his *last purchase*, the consumer proceeds to purchases this optimal product. If the utility from the optimal product in $C_m(t)$ is not sufficiently high compared to his last purchase, he does not make a purchase in period t. With this, we introduce the concept of the *conservative consumer* – one who prefers not to buy the latest variant in the market, but will upgrade only if there is sufficient incentive to do so. This is done using a *global* parameter $0 \leq \gamma \leq 1$, such that $y(t)$, the optimal choice of consumer m in period t is given by,

$$y(t) = \begin{cases} \arg\max_{j \in C_m(t)} U_m^j(t), & \text{if } C_m(t) \neq \phi \text{ and } \dfrac{U_m^{y(t)} - U_m^{y(t-1)}}{U_m^{y(t-1)}} \geq \gamma \\ \\ y(t-1), & \text{otherwise.} \end{cases} \tag{9}$$

The definition in (9) illustrates the following choice rule: a consumer will not make a new purchase if the consideration set is empty or if none of the products within the set are good enough to warrant a new purchase. A purchase will only be made if there is at least one product within the consideration set which increases his utility sufficiently, as determined by the utility threshold γ. A higher value of γ indicates a more conservative market, whereas a lower value indicates a market where consumers try out new products more readily. Given the way consumer choice has been specified in (8) and (9), the demand for any new product i can now be represented as $D_i(\mathbf{x}(t), \mathbf{p}(t)|\mathbf{x}(t-1), \gamma)$, where $\dfrac{\partial D_i}{\partial x_i} \geq 0$, $\dfrac{\partial D_i}{\partial p_i} \leq 0$ and $\dfrac{\partial D_i}{\partial \gamma} \leq 0$ for all $i \in N$.

4. Results

To begin with we ignore the dynamic aspect of the model presented above, and examine the outcome when the interaction between firms is restricted to a single period. The primary analytical result of the static model, presented in Proposition 1, provides an useful benchmark and a starting point for the analysis. For details of how Proposition 1 was derived mathematically, see Appendix A.

Proposition 1. *Considering a single period of interaction only, if competitive firms undertaking open innovation are each endowed with a certain level of technology, then the firm with the highest technology endowment weakly prefers to be in the PL regime, while others with lower technology endowments will unambiguously prefer to be in the OS regime.*

Proposition 1 indicates that there is a clear preference ordering among firms, when it comes to a choice between joining an OS consortium versus choosing the PL route, depending on the initial endowments of technology. Firms in the market who possess the highest endowments, always prefer to retain the rights to their intellectual property in this one period static model. All other firms prefer the OI route to sharing technology. Once the dynamic interactions between firms are introduced, this result changes significantly.

4.1. Dynamic model setup

The agent based simulations are used to test the impact of changing a set of input variables on a set of outputs for both OS and PL. The primary inputs considered were, γ, N, M. Additionally, the impact of r, Φ and ρ are also examined in the case of PL. The outputs or the variables representing outcomes of each model are $R_i(t), x_i(t), \Sigma_i(t)$, market penetration[12] and profit of firm i in t, and market concentration $H(t)$ (the normalized Herfindahl-Hirschmann index) – for all firms i and for all periods t. In addition, a set of control variables were included, those whose values are fixed in all simulations, and do not form the basis of any experimentation.

Based on three alternative values of the 3 input variables, the OS simulation model was composed of 27 experiments[13]. The PL model had 6 input variables, each with three alternative values, thus resulting in 729 experiments. In each experiment, the simulations were repeated 30 times to account for random variations, and in each repetition, the simulation ran for 400 discrete periods (time steps).

Table 1 lists all the parameters of model, their types and value ranges used in experiments, categorised as input, control and output variable. All computer codes can be made available on request. All the data generated from the simulation based experiments were stored and analyzed using standard statistical methods. Further details about the agent based simulation set up are provided in Appendix C, and the descriptions of the data generated from experiments along with nature of analyses are provided in Appendix D.

4.2. Comparisons between OS and PL

Table 2 presents the comparisons between OS and PL on the basis of six outcomes – aggregate technology, R&D investments, likelihood of adopting a competitor's technology, firm level profit, market penetration, market concentration. Column 2 provides the equivalent empirical measure, and Column 3 states the *difference* between the specific OS and PL outcome, as measured across each experiment. A positive difference implies that the OS outcome is greater in value than the PL, and vice versa. The significance values are on the basis of the non-parametric Wilcoxon Signed Rank test.

4.2.1. Firm Profit

The first key result of the dynamic model is captured in Proposition 2.

[12]Market penetration of a firm i at a given period is defined as the proportion of consumers currently *using* a product manufactured by firm i (but may not necessarily have been purchased in that period). Market penetration provides a more accurate picture of product usage as opposed to market share. Market penetration takes into account two additional aspects which share does not – first, consumers who may have not bought anything in the current period but are continuing to use a firm's older generation product and second, consumers who may have never bought any product at all. The Herfindahl-Herschmann index is computed on the basis of market concentration as well.

[13]Each experiment is a unique combination of parameter values. Since there are 3 parameters, and each can have 3 possible values, the total number of experiments is $3^3 = 27$.

Table 1: Independent, Control and Dependent variables for each model

Variable Type	Variable name	Value/Range/Description
Independent	*OS:*	
	numOfConsumers (M)	{1000, 3000, 5000}
	numOfFirms (N)	{3, 5, 7}
	utilityThreshold (γ)	{0.001, 0.1, 0.5 }
	PL: OS variables plus ...	
	probOfInfringe (Φ)	{0.1, 0.5,0.9}
	royalty (r)	{0.1,0.5, 0.9}
	penaltyInfringe (ρ)	{0, 50, 100}
Control	*OS:*	
	R_{min}	1
	costOfTechnology (c)	20
	defaultX ($x_i(0)$)	10
	defaultPrice ($p_(0)$)	1
	strategyUpdate (λ)	0.01
	upperEpsilon ($\bar{\epsilon}$)	2
	PL: OS variables plus ...	
	fixedFee ($\overline{L}$)	5
Dependent	$R_i(t)$	Investment made in t by firm i
	$x_i(t)$	Technology level attained in t by firm i
	$\Omega_i(t)$	Strategy profile in t of firm i
	marketPenetration of i in t	Proportion of consumers who use firm i's product in t
	currentProfit of i in t	Profit earned by firm i in period t
	$H(t)$	The normalised Herfindahl-Hirschmann Index of concentration in period t

Proposition 2. *Within a dynamic multi-period OI setting, firm profits operating within an OS framework are at least as high as those within PL.*

On average, firms engaged in OS earn higher profit than those in PL. In contrast to the static model presented above, this result indicates that in a dynamic setting firms are better off within an OS arrangement. Note that there are no high or low type firms *a priori* in this model, given that different firms can emerge as high or low types at different periods, conditioned on past innovation performance. What this result indicates is that, *ex ante* all innovating firms would be better off under OS than under PL.

For firms with lower technology levels at any given point in time, OS is clearly better than PL as they are able to access the superior technology from the market leader. However, the key

Table 2: Comparison of outcomes in OS and PL. Results from Wilcoxon Signed Rank tests on pair wise comparison of means across all experiments.

Outcome	Empirical variable(s) in each simulation	Difference between OS and PL
Aggregate technology outcome	$x_1(400)$	Not significant
Investment in R&D	$\frac{1}{400}\sum_{t=1}^{400} R_1(t)$	Negative **
Likelihood of adopting competitor's technology	OA: $s^1(400)$ PA: $s^1(400) + s^2(400)$	Negative***
Average profit of any given $i \in N$	Profit of firm 1 averaged over $t = 1 \ldots 400$	Positive ***
Market penetration of any given $i \in N$	Average of proportions of consumers using 1's product at each t	Not significant
Market concentration overall	$\frac{1}{400}\sum_{t=1}^{400} H(t)$	Negative***
Market concentration with large market size ($M = 5000$)	Same as above	Positive***

difference that the dynamic setting makes is that a firm with superior current technology at a given time is now able to sacrifice a portion of their current revenue (in the form of royalties and penalty payments from rivals) in exchange for potential access to even better technology in the future, through innovation activity of rivals. What this result indicates that for the latter, the benefits of potential future access to rivals' technology more than compensates the loss in current revenue.

In our model, as the OS paradigm is the limiting case of the PL with $r = \Phi = \rho = 0$, it can be assumed that this superiority of OS over PL in terms of firm profit will be valid for values of r, Φ, ρ above certain thresholds of these parameters. It is reasonable to assume that any further weakening of the patenting regime by lowering individual parameters or through a combination of these will result in equivalence of both regimes with respect to profits.

4.2.2. Market Concentration

Another important distinction between the two regimes can be seen in the average market concentration achieved by firms in each, as captured in Proposition 3.

Proposition 3. *Within a dynamic multi-period OI setting, while concentration is higher under the PL framework than under OS in general, for markets where number of customers is sufficiently* *large, PL leads to lower concentration.*

The simulations reveal that the average market concentration of firms, in terms of the normalized Herfindahl-Hirschmann index (HHI), is overall lower in OS than in PL. This implies that when competing firms engage in OS and agree to share knowledge and technology freely amongst themselves, individuals are less likely attain and sustain a dominant market position for a length of time. Even if one firm is able to acquire a dominant market position (possibly due to a significant technological breakthrough), this position is short lived and other firms are quickly able to catch up – either through seamless knowledge and technology exchanged within the consortium or through further random technological breakthroughs. However, in those subsets of experiments where the market size (M) is very large, the concentration under PL is generally lower that OS, thus ensuring more equitable distribution amongst the firms.

For smaller to medium sized markets, PL encourages the emergence of localized monopolies, which are able to sustain themselves for a longer time than they are able to under OS. Without free exchange of technology among firms, each of the smaller players either have to sacrifice a part of the profit to gain access to the superior technology immediately or wait for their own technology to catch up with that of the market leader's. The former lowers the investment available for research in the next period, by which time the market leader would have progressed even further, and the latter implies a time gap before a smaller player is able to catch up. In both cases, lower profits in PL for the smaller players imply a longer interval of time in which the market leader maintains dominance. But if the market size is large, even with a dominant player present, smaller firms are able to generate enough profit from their sales to invest significant amounts back into research – which enables them to catch up faster.

4.2.3. Innovation behaviour

The following propositions capture important innovation related behaviours of firms under the two OI frameworks.

Proposition 4. *Within a dynamic multi-period OI setting, final technological outcomes are similar under both OS and PL frameworks.*

Proposition 5. *Within a dynamic multi-period OI setting, the rate of technology adoption between firms is higher under PL than OS.*

Proposition 6. *Within a dynamic multi-period OI setting, average amount of R&D investment per firm is lower in OS than in PL.*

According to Proposition 4, aggregate technology levels achieved are similar under both OS and PL, that is no statistically significant difference could be found between these two regimes under all possible parameter combinations. This may be explained by the fact that the knowledge about the market leader's technology is free in both regimes (but the technology itself not is not in PL) and technologically backward firms would be able to keep up with the front runners even if it comes at a cost (licensing fees and penalties under PL), as long as they are aware of the difference in knowledge.

Proposition 5 implies that, even though firms have the option of adopting their rivals' technology in their own products freely in the OS setting, they do so *less frequently* than in PL. This result is non-intuitive, but given that OS and PL do not encourage differences in aggregate technology levels, can be explained. Since market leadership and dominance is more likely under PL, smaller players in the market have more incentive to adopt the leader's technology (either by licensing or by infringing the patent) in order to reduce the technology gap and market share difference. As the PL regime is weakened and moves towards OS, this incentive for catch up decreases, as firms are less likely to be dominant as well, and hence the rate of cross adoption of each others' technology falls.

Finally, Proposition 6 states that on average, firms in OS invest *less* in R&D than firms in PL. This is interesting and significant, especially when combined with the invariance between the two on technology outcomes. This indicates that OS is a relatively *more efficient* system of innovation from the industry's point of view. Firms can achieve similar technology levels but at a lower cost, implying that the PL system induces additional expenditure of R&D resources. This expenditure can come from a number of sources – direct inter-firm payments (licenses or penalties) or indirect (duplication of innovations due to lower incentives to use of a rival's technology, even if it is superior to one's own).

Note that market concentration, technology levels, R&D investments and adoption rates are all co-evolving factors in this complex dynamic system. Hence it is difficult to attribute causality of one on another, but it is likely that these factors feedback on each other to a large extent through mechanisms just described, resulting in the above outcomes.

4.3. Impact of market characteristics on OI

We now examine the impact of key market characteristics on the dynamics of OI. We begin by evaluating the impact of the level of consumer conservativeness γ, that is, preference of the market towards newer technologies.

4.3.1. Technology trajectory and market dominance

Two interesting dynamic properties of an OI based industry can be seen from the simulations. First, is the dependence of the *shape* of technology trajectory on the value of γ, presented in Proposition 7.

Table 3: Impact of inputs on aggregate outcomes - OS. Relative size and direction. ++ and – indicate relatively large positive and negative impact respectively.

	Aggregate Technology Outcome $x_1(400)$	Likelihood of using competitors' technology $s^1(400)$	Likelihood of using own technology $s^2(400)$	Average market penetration	Investment $\frac{1}{400}\sum_{t=1}^{400} R_1(t)$	Market concentration $\frac{1}{400}\sum_{t=1}^{400} H(t)$
γ	– –	– –	++	– –	– –	– –
M	+	+	–	–	+	–
N	-	++	–	–	–	+

Table 4: Impact of inputs on aggregate outcomes - PL. Relative size and direction. ++ and – indicate relatively large positive and negative impact respectively.

	Aggregate Technology Outcome $x_1(400)$	Likelihood of licensing $s^1(400)$	Likelihood of infringing $s^2(400)$	Likelihood of using own technology $s^3(400)$	Average market penetration	Investment $\frac{1}{400}\sum_{t=1}^{400} R_1(t)$	Market concentration $\frac{1}{400}\sum_{t=1}^{400} H(t)$
γ	– –	++	– –	++	– –	– –	– –
M	++	+	+	–	+	+	+
N	–	++	+	– –	– –	– –	+
Φ	+	– –	++	– –			
ρ		+	–	+			
r		– –	+	++			

Proposition 7. *Within a dynamic multi-period OI setting, lower values of γ result in a stepwise technology trajectory for firms, with periods of low technological progress, followed by short intervals of rapid jumps in technology. Increasing value of γ makes the technology trajectory smoother and monotonic.*

Second is the dependence of the dominance hierarchy among firms on γ, presented in Proposition 8.

Proposition 8. *Within a dynamic multi-period OI setting, lower values of γ coincide with more frequent emergence of dominant firms for finite intervals of time, when it is able to capture large share of the market. Increasing value of γ results in more equitable distribution of market shares.*

Propositions 7 and 8 are reflected in Figure 1. It captures the impact of γ on the technology trajectories (left) and levels of market penetration (right) of a 3-firm industry where OI is imple-

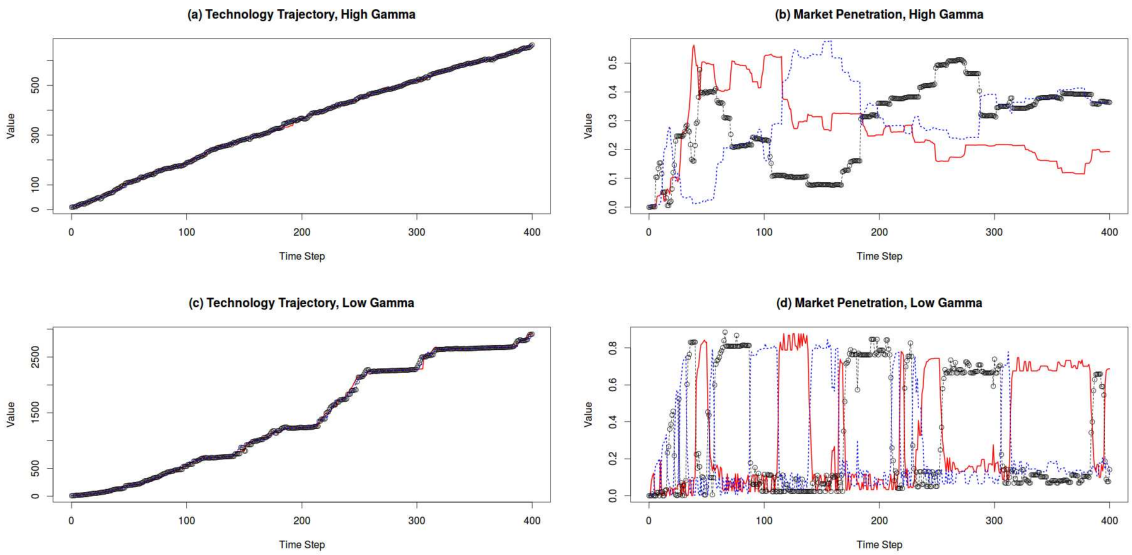

Figure 1: Technology trajectory ($x(t)$) and market penetration of firms from two random simulation runs with different γ under OS with 3 firms. Figures (a) and (b): $\gamma = 0.5$; Figures (c) and (d): $\gamma = 0.001$.

mented. This particular figure represents one sample simulation run from two randomly chosen OS experiments, where the top row represents a high $\gamma = 0.5$ and the bottom row represents a low $\gamma = 0.001$. Graphs for random draws from the PL experiments are very similar.

Interestingly, the shape of the technology trajectory can be linked to the presence or absence of a dominant firm in the market. Under low γ, those periods where the trajectory is relatively flat (with incremental technology growth), are also the ones where a dominant firm exists in the market (Figures 1 (b) and (d)). This implies that, for an industry with low values of γ, a firm who is a dominant player in the market in terms of market penetration, also *slows down* the overall pace of technology growth. It is only when a rival is able to come up with a major innovation that the dominance hierarchy shifts, and of course coincides with a large jump in the technology trajectory. On the other hand, when γ is high, the technology trajectory in the industry is smooth (Figure 1(a)) and this coincides with no firm having a clear dominance in the market for any length of time (Figure 1(b)).

The above results imply a complex non-linear relationship between the consumer characteristics, nature of nature of innovation with OI and dominance hierarchy between firms. With less conservative consumers (low γ), who are more ready to try out new technologies, a firm is able to dominate the market relatively easily when they come up with a radical innovation. However, the presence of this dominant player slows down the aggregate technology growth as a large proportion of the consumers get locked into its product, while the rest of the players gradually catch up with the market leader. In time, technology shocks will disturb this "steady state" and jumps in the technology trajectory will occur and new dominance hierarchy introduced. With more conservative consumers, firms find it difficult to capture large sections of the market and dominate, and hence the trajectory is smoother. These patterns are qualitatively identical for both OS and PL frameworks, implying that the complex link between consumer characteristics, market concentration and technology outcomes is an universal feature of OI.

4.3.2. Aggregate technology and market outcomes

Finally, we explore the relationship between the independent and dependent variables of the dynamic model. As explained in Appendix D, this done through a series of linear regression models. The results are presented in Tables 3 (for the OS model) and 4 (for the PL model). In both tables, instead of the actual coefficient and p-value, the sign and relative magnitude of the relationship is expressed by '+' or '–' signs. For coefficient sizes which are relatively larger (by two orders of magnitude or more), we use the '++' and '–' symbols. Given that each experiment was repeated 30 times, the OS model provided 810 observations and the PL model provided 21,870 observations to run the regressions on.

The degree of conservativeness of consumers γ is an important influence on OI outcomes. Across both OS and PL, higher γ reduces aggregate technology levels, overall investments in R&D and market concentration. As consumers become more conservative, firms are less likely to reap high profits from new innovations, which reduce the overall levels of R&D investments, and thus causing a reduction in the likelihood of large technological breakthroughs as well as average levels of market penetration.

The implications are that when competitors are able to share knowledge and technology amongst themselves (through OS or PL), there exists a link between *potential cooperation* in upstream research and innovation, and the downstream *competition* in the product market, but this link is a complex one and may be heavily influenced by the preferences of consumers in the market. However, γ is not the only parameter which influences technology outcomes and competition in the model.

Another important factor is the number of competing firms (N). An increase in N *reduces* aggregate investment and technology outcomes but leads to increase in market concentration. This result is somewhat counter-intuitive, as a larger size of the consortium is expected to correlate with increased chances of technology growth and lower market concentration. But the link between profits and investment is crucial in explaining this result. All else equal, larger number of competitors imply a lower market share which in turn implies lower investments in research overall. This explains the lowering of aggregate technology outcomes as N increases. The impact on market concentration can also be explained, but in a more dynamic context. A higher number of competitors imply a lower profit if all else is equal. Hence when a single large technological breakthrough captures a large portion of the market, the smaller players with less profit to reinvest in innovation, find it difficult to catch up with the current market leader. This increases the length of the period which the market leader is able to dominate, reducing competition and increasing concentration. This is true even in the OS framework where the market leader's technology is freely available. It takes time for firms to embed this new technology and improve it through further research, while the market leader keeps on innovating on a larger or advanced knowledge base.

Finally, the size of the market (M) has significant consequences for the model outcomes as well. Overall, as M increases, this has a positive effect on aggregate technology outcome, aggregate investment and a negative effect on market concentration. Qualitatively, this is similar to *decreasing* N, which is reverse of what is explained above.

5. Discussion and Conclusion

In a technology driven industry where firms are attempting to compete through newer and better products, it is imperative from a resource perspective that knowledge creation effort is not unnecessarily duplicated across different organizations (Gambardella and Panico, 2014; Hall et al., 2013). Any OI based framework, such as OS and PL, can provide a mechanism by which externally created knowledge could be internalized (Hagedoorn and Wang, 2012; Han et al., 2012). While the former enables access to external knowledge and technology adoption costless due to common ownership of intellectual property within a consortium of firms, the latter provides property rights to the inventor and consequently makes cross adoption of technology costly (although knowledge about the technology is usually free). The analysis above provided rich theoretical insights on the similarities and differences between both, in terms of long term implications on industry, firms and market structure.

From the industry's point of view, our models of OI predicts both mechanisms to be indistinguishable in terms of aggregate technology *outcomes*, i.e. an industry characterised by either one of the regimes will achieve similar levels of technology growth. However, differences emerge in the context of individual firms, with respect to profit, R&D investments and the impact on market concentration. OS offers three strategic advantages to firms over PL – first, on average firms enjoy higher levels of profits over the entire innovation cycle; second, it makes the innovation process more efficient and third, it encourages a more level playing field than PL in terms of market penetration, especially when the market is small or restricted and/or number of competitors is high. Hence, when all else is equal, smaller innovative firms may have a greater incentive to participate in an OS consortium than using the PL route. They would be able to utilize resources better and have higher chances of longer term survival, especially so if the potential market is limited. However, with an increase in the potential market size, this advantage of OS over PL is gradually eroded – as a bigger playing field allows smaller firms space to grow. This also serves as an important lesson for entrants into technology driven industries – once the competition has been accounted for, potential market size is critical in determining whether there is any added benefit from moving towards openness, particularly the OS framework.

Although OI collaborations are becoming more common, these arrangements are yet to become gain a foothold in many industries. In fact, many industries, such as Pharmaceuticals, Biotechnology, Consumer Electronics, Food and Agriculture, are dominated by large companies utilizing the PL system extensively. Given how well established the PL system is in these industries, it may be difficult to organize collaborative R&D efforts using open sourcing. Previous research shows that smaller firms do prefer utilizing alternative informal and more open routes of IP management, instead of the formal PL structure (Freel and Robson, 2017; Hall et al., 2014). Our paper reinforces this by showing that industries adopting the OS route could result in tangible benefits for firms. For firms already operating within a PL regime, it is interesting to ask what incentives can be provided for them to shift towards OS by lowering patent barriers. While our model cannot answer this question directly, it does provide some indicators on why firms will *jointly* consider adopting OS.

OS also provides an unique opportunity for smaller firms to appropriate the benefits of shared knowledge without having to set up or negotiate costly barriers. While a pure OS set up with multiple partners may be difficult to implement, alternative arrangements are possible. Instead of a choice between a pure OS versus pure PL framework, a middle path could be the use of *patent pools* as a collaborative IP management system. As noted by a number of previous contributors[14], patent pools can provide benefits in terms of reduction of transaction costs, easing the path of complementary technologies to develop, reducing post infringement litigation costs and increasing innovation potential. The evidence on the impact of such pools on downstream innovation and competition is mixed, but in terms of our model, they can reduce the negative effect of sustained concentration and the corresponding effect on slower technology evolution in periods of high concentration.

Yet another important implication of our models is the interaction between consumer preferences and innovation outcomes. We found that the nature of consumers, in terms of conservativeness towards new products and technologies, can drive the dynamics and evolution of the technology trajectory and pattern of investments in R&D. We also saw that consumer preferences are able to interact with the changes in immediate market structure and concentration, which in turn have an impact on immediate growth rates in technology. This is a novel finding which has important implications on firms' strategies irrespective of whether they follow the OS or PL routes of OI. While

[14]See Dequiedt and Versaevel (2013) for a dynamic model of patent pool formation. Additionally, a number of empirical studies have examined the impact of such pools using retrospective data, such as Lampe and Moser (2010, 2011, 2012), Baron and Pohlman (2012).

the model assumes the same value of γ for all consumers in the market, in reality a continuum of various levels of conservativeness is expected to be present along with an associated distribution. Markets where the distribution is asymmetric, that is, they have a higher proportion of one type of consumers, are likely to exhibit different technology outcomes compared to markets which are more balanced or markets where the asymmetry is towards the other end of the distribution.

The size of competition is an important factor as well in this model. For a given market size, presence of a large number of firms actually reduces aggregate technology outcome and increases the chances of a dominant player emerging. This has important strategic considerations for a set of firms jointly agreeing to share knowledge through a consortium. If the introduction of a new member in the consortium increases the size of the potential market for all members, this can have beneficial effects in terms of technology outcomes and market concentration. For instance, a firm might have been operating in a different geographical location or in a separate non-competitive market previously. Once it joins the consortium, this opens up a new market for the rest of the members, and the model predicts that it will lead to a better social outcome in terms of technology growth and market distribution.

While this model is one of the first of its kind to examine the dynamic impacts of the OI paradigm using the complex adaptive systems view, it does have its limitations. For one, it does not allow for dynamic entry and exit of firms as the number of participants is fixed at the outset. While this is ongoing research for the authors, we do expect that it will have an impact on the downstream outcomes if strategic entry or exit is allowed in the model. Secondly, it does not allow the *co-existence* of different intellectual property frameworks in the same model. It would be interesting to examine the dynamic properties of such a model which allows this, especially from the point of view of strategy. Thirdly, we do not explore strategic alliances between vertically linked firms in this paper, but only concentrate on horizontal competitors. The ability to form vertical relationships and its corresponding impact would be an important area to explore within this conceptual framework. Finally, we do not examine the day to day innovation management by firms, but concentrate on strategic choices on innovation made individually or jointly. The former would require behavioural models focussed on managing individual R&D projects and the project portfolio. That level of detail would make the models more complicated and potentially intractable, and hence are not explored.

5.1. Conclusion

The theoretical models presented here make important contributions, to the open innovation literature (Bogers et al., 2018; Chesbrough, 2017), and to the wider literature in innovation platforms as complex systems (Sorenson et al., 2006), through a set of testable propositions and results, built upon the outputs of the experimental analysis. As large scale OI initiatives become more popular in industry, the equivalence between OS and PL in technology outcomes is an interesting point to explore empirically, especially in reference to the strength of the PL regime itself. A related aspect is the superiority of the OS regime in terms of efficiency of investments. The link between consumer preferences and dynamics of the technology trajectory is another relevant testable theorem, and has relevance to strategic decisions by firms in specific markets.

In conclusion, the model and results presented above represent a preliminary theoretical attempt to understand the dynamic properties of an industry with firms forming complex knowledge sharing linkages in the process of innovating. It goes to the heart of what it means to be within an open innovation set up, what the behavioural micro-foundations and their implications are, and how different variants of open innovation compare against each other. The model explores the impact of a number of parameters of the model through agent based simulations, comparing the outcomes of a OS paradigm to a standard PL framework. The model throws up a number of emergent properties of such systems, and makes interesting comparisons between the two alternative models of innovation.

Appendix A. Static Model

Here we present the detailed analysis of the one period static model, which is used as the benchmark. We adopt a game theoretic approach, where we derive the Nash equilibrium of the model and examine its properties.

Following the notation developed in Section 3, each firm i is endowed with an initial technology x_i^0, which may be used as the base technology (instead of $\tilde{x}_i$), using a similar innovation process described in (1). Each firm is able to either use his own endowment or that of a rival. R_i^* is once again algorithmically determined. Firm i's demand is now represented as $D_i(\mathbf{x}, \mathbf{p}|\mathbf{x^0}, \gamma)$, where $\mathbf{x}, \mathbf{p}$ and $\mathbf{x^0}$ are the vectors of x_i, p_i and x_i^0, where the partial derivatives retain the same signs as described above.

The following additional but non-restrictive assumptions on the nature of $R_i^*, T(\cdot) and D(\cdot)$ needed to be made for deriving the analytical results.

Assumption 4. *The relationship between i's technology endowment and R_i^* is weakly negative, i.e.*

$$\frac{\partial R_i^*}{\partial x_i^0} \leq 0.$$

Assumption 5. *The slope of the technology production function $T(R_i, \epsilon)$ with respect to R_i is positive and steeper than the positive inverse slope of the investment function, i.e.*

$$\frac{\partial T}{\partial R_i} \geq -\frac{1}{\partial R_i^* / \partial x_i^0}.$$

Finally, we require that the demand for i's product $D_i(\mathbf{x}, \mathbf{p}|\mathbf{x^0}, \lambda)$ has the following property.

Assumption 6. *$x_i \left(D(\mathbf{x}, \mathbf{p}|\mathbf{x^0}, \lambda) - 1\right)$ is increasing in x_i.*

Price is also algorithmically set as before, as a positive mark up over technology costs, i.e. $p_i = c.x_i + \Delta$, where $\Delta \geq 0$.

The above describe one period games G^{OS} and G^{PL} for the OS and PL frameworks respectively. Each firm observes their endowment, simultaneously chooses an available strategy, invests and sets a price and finally earns a payoff defined in (3).

Let H be the set of firms with the highest technology endowment among all firms:

$$H = \left\{ i \in N : h = \arg\max_i x_i^0 \right\}$$

Let $L \subset N$ be the set of all the rest which have endowments less than the firm(s) with the highest endowment, i.e. which do not belong to set H. For brevity, we label all firms in H as the high type and the rest as low type. We are now ready to state the main results of the static model.

Lemma 1. *Under OS, the game G^{OS} has a unique pure strategy Nash equilibrium, where the high type firm has a dominant strategy s^2, that is, use their own technology endowment, while all low type firms choose s^1, and use the the high type's endowment.*

Lemma 2. *Under PL, the game G^{PL} has a pure strategy Nash equilibrium, where the all high type firms $h \in H$ choose s^3, that is, use their own technology endowment. Any low type firm l would choose s^1, that is license the high type's endowment if and only if,*

$$x_h^0 - x_l^0 > \frac{rD_l'}{\Phi.\rho}$$

where $D_l' = D_l(\ldots, \tilde{x}_l', \ldots, \mathbf{p}|\mathbf{x}, \lambda)$, is the demand of l's product if he adopts x_h^0.

The proofs are given in Appendix B. Lemma 1 reveals that G^{OS} has a unique pure strategy Nash equilibrium where all high type firms choose to use their own technology, while all the rest costlessly copies the high type's technology. Lemma 2 on the other hand reveals that the equilibrium is not as straightforward, but depends on the underlying parameters, specifically the technology endowments of h and l. The high type still prefers to use his own endowment as s^3 dominates the other two strategies. For any low type firm, the *licensing* strategy s^2 dominates over others if and only if the difference with the high type's endowment is sufficiently high. In such cases, a low type firm can sacrifice the licensing fee profitable. If the condition is not met, then the equilibrium choice is between s^2 and s^3 and depends on the values of Φ and ρ.

Theorem 1. *If competitive firms undertaking open innovation are each endowed with a certain level of technology, then the firm with the highest technology endowment weakly prefers to be in the PL regime, while others with lower technology endowments will unambiguously prefer to be in the OS regime.*

Theorem 1, expressed as Proposition 1 in the main text, indicates that there is a clear preference ordering among firms, when it comes to a choice between joining an OS consortium vs choosing the patent licensing route, depending on the initial endowments of technology. For firms in the market who possess the highest endowments, always prefer to retain the rights to their intellectual property in this one period static model. All other firms prefer the OS route to sharing technology.

Appendix B. Proofs

As a matter of notation, define D_i' as the demand for i's product if he adopts anything *other than* his own endowment x_i^0 as the technology base. Correspondingly, x_i' is the resulting new technology from investment of R_i', which is what gives rise to demand D_i'. This notation is used in all proofs below.

Appendix B.1. Proof of Lemma 1

Consider any randomly chosen firm $h \in H$ and $l \in L$, with endowments x_h^0 and x_l^0 respectively. Each firm can choose from one of two strategies $\{s^1, s^2\}$. First consider firm h's equilibrium strategy choice. His profit as a function of strategy choice is given by:

$$\pi_h(s^1) = (c.\tilde{x}_h' + \Delta)D_h' - c.\tilde{x}_h' - R_h'$$
$$\pi_h(s^2) = (c.\tilde{x}_h + \Delta)D_h - c.\tilde{x}_h - R_h.$$

Now,

$$\pi_h(s^2) - \pi_h(s^1) = c\,[\tilde{x}_h(D_h - 1) - \tilde{x}_h'(D_h' - 1)] + \Delta(D_h - D_h') + (R_h' - R_h).$$

The above expression is positive as all terms on the right hand side can be shown to be positive. First of all, $\tilde{x}_h \geq \tilde{x}_h'$ given Assumption 5. This, along with Assumption 6 ensures that the first term is positive. Given the specification of demand, the second term is positive as well. Finally, the third term is positive given Assumption 4. Hence $\pi_h(s^2) - \pi_h(s^1) > 0$ irrespective of choices made by other firms and this implies that a high type firm has a dominant strategy, which is to choose s^2. Given the high type firm's dominant strategy, consider any firm $l \in L$. Firm l's profit as a function of strategy choice is given by:

$$\pi_l(s^1) = (c.\tilde{x}_l' + \Delta)D_l' - c.\tilde{x}_l' - R_l'$$
$$\pi_l(s^2) = (c.\tilde{x}_l + \Delta)D_l - c.\tilde{x}_l - R_l.$$

As before,

$$\pi_l(s^1) - \pi_l(s^2) = c\,[\tilde{x}_l'(D_l' - 1) - \tilde{x}_l(D_l - 1)] + \Delta(D_l' - D_l) + (R_l - R_l') > 0$$

following from $\tilde{x}_l' \geq \tilde{x}_l$ given assumptions 4, 5 and 6. This completes the proof.

Appendix B.2. Proof of Lemma 2

Once again consider randomly chosen firms $h \in H$ and $l \in L$, with endowments x_h^0 and x_l^0 respectively. Each firm can choose from one of three strategies $\{s^1, s^2, s^3\}$. Consider firm h's profit as a function of strategy choice:

$$\pi_h(s^1) = (c.\tilde{x}_h' + \Delta - r)D_h' - c.\tilde{x}_h' - R_h'$$
$$\pi_h(s^2) = (c.\tilde{x}_h' + \Delta)D_h' - c.\tilde{x}_h' - R_h' - \Phi.\rho.(x_h^0 - x_l^0)$$
$$\pi_h(s^3) = (c.\tilde{x}_h + \Delta)D_h - c.\tilde{x}_h - R_h$$

Now,

$$\pi_h(s^3) - \pi_h(s^1) = c\left[\tilde{x}_h(D_h - 1) - \tilde{x}_h'(D_h' - 1)\right] + \Delta(D_h - D_h') + rD_h' + (R_h' - R_h)$$

As $\tilde{x}_h > \tilde{x}_h'$ given assumption 5, and given assumptions 4 and 6, each term in the above expression is positive. Hence $\pi_h(s^3) - \pi_h(s^1) > 0$ for any strategy chosen by other firms. Now consider

$$\pi_h(s^3) - \pi_h(s^2) = c\left[\tilde{x}_h(D_h - 1) - \tilde{x}_h'(D_h' - 1)\right] + \Delta(D_h - D_h') + \Phi.\rho.(x_h^0 - x_l^0) + (R_h' - R_h).$$

For the same reasons as mentioned above, all terms in this expression are positive, and hence $\pi_h(s^3) - \pi_h(s^2) > 0$, for any strategy chosen by other firms. Hence, s^3 is a strictly dominant strategy for all firms in H. Given this, consider the strategy choice by any firm $l \in L$.

$$\pi_l(s^1) = (c.\tilde{x}_l' + \Delta - r)D_l' - c.\tilde{x}_l' - R_l'$$
$$\pi_l(s^2) = (c.\tilde{x}_l' + \Delta)D_l' - c.\tilde{x}_l' - R_l' - \Phi.\rho.(x_h^0 - x_l^0)$$
$$\pi_l(s^3) = (c.\tilde{x}_l + \Delta)D_l - c.\tilde{x}_l - R_l.$$

Once again, it can be shown that given our assumptions and specifications of demand, $\pi_l(s^1) - \pi_l(s^3) > 0$. However, $\pi_l(s^1) - \pi_l(s^2) > 0$ if and only if $x_h^0 - x_l^0 > \dfrac{rD_l'}{\Phi.\rho}$, as all other terms in the expansion are equal. This completes the proof.

Appendix B.3. Proof of Theorem 1

Consider any high type firm $l \in L$, and his preference between OS and PL regimes. Let $\pi_k^z(s', s'')$ be the profit of firm $k \in \{H, L\}$ in regime $z \in \{OS, PL\}$, when he chooses s' and the rival firm of a different type chooses s''. Based on Lemma 1, firm l's profit under OS is:

$$\pi_l^{OS}(s^1, s^2) = (c.\tilde{x}_l' + \Delta)\, D_l' - c.\tilde{x}_l' - R_l'.$$

Firm l's equilibrium profit under PL depends on his strategy choice, and based on Lemma 2 these are:

$$\pi_l^{PL}(s^1, s^3) = (c.\tilde{x}_l' + \Delta)\, D_l' - c.\tilde{x}_l' - R_l' - rD_l'$$
$$\pi_l^{PL}(s^2, s^3) = (c.\tilde{x}_l' + \Delta)\, D_l' - c.\tilde{x}_l' - R_l' - \Phi.\rho.(x_h^0 - x_l^0)$$
$$\pi_l^{PL}(s^3, s^3) = (c.\tilde{x}_l + \Delta)\, D_l - c.\tilde{x}_l - R_l.$$

Hence, $\pi_l^{OS}(s^1, s^2) - \pi_l^{PL}(s^1, s^3) = rD_l' > 0$ and $\pi_l^{OS}(s^1, s^2) - \pi_l^{PL}(s^2, s^3) = \Phi.\rho.(x_h^0 - x_l^0) > 0$. Now $\tilde{x}_l < \tilde{x}_l'$ given assumption 5. Additionally, given assumptions 4 and 6 we have,

$$\pi_l^{OS}(s^1, s^2) - \pi_l^{PL}(s^3, s^3) = c\,[\tilde{x}_l'(D_l' - 1) - \tilde{x}_l(D_l - 1)] + \Delta(D_l' - D_l) + (R_l - R_l') > 0$$

Hence firms of type l will always prefer OS over PL. Now firm of type $h \in H$ always chooses to use own endowment in equilibrium, under both OS and PL. Hence,

$$\pi_h^{OS}(s^2, s') - \pi_h^{PL}(s^2, s') = \begin{cases} -rD_l' < 0, \text{if, } s' = s^1 \\ -\Phi.\rho.(x_h^0 - x_l^0) < 0, \text{if, } s' = s^2 \\ 0, , \text{if, } s' = s^3. \end{cases}$$

Hence, any firm of type h weakly prefers PL over OS.

Appendix C. Simulation setup

All simulations were implemented in the agent based framework Netlogo[15]. All simulations had two types of agents, firms and consumers, following behavioural models specified above. At the beginning of each run, each consumer agent is randomly seeded with the following parameters: $\beta_m \in (0, 1)$, $x_m \in (0, 100)$, $p_m \in (0, 2000)$. All were drawn from uniform distributions. Firms were seeded randomly with an initial value of technology stock, $x_i \in (0, 25)$, again from an uniform distribution. Additionally, the random technology shock $\epsilon_i(t)$ was drawn from an uniform distribution in $(0, \bar{\epsilon})$, for each firm separately at each time step. The technology production function used in the simulation was $T(R) = R^{0.5}.\epsilon(t)$ for $R \in [R_{min}, \infty]$, a concave monotonic function. Simulations are carried out for various values of $\gamma, \bar{\epsilon}, M, N$ and other regime specific variables (for PL), all of which were input variables in the model. In addition to these, a number of other parameters were kept fixed for all experiments – which are termed as control variables in the model (see Lorscheid et. al. 2012 for detailed classification of input, output and control variables). A 2^k factorial analysis of the model

[15] Netlogo is a well known open source Java based agent based modelling framework. We used Netlogo 5.0.2 for designing, set up and experiments. More details can be found at https://ccl.northwestern.edu/netlogo/. All computer codes can be made available upon request.

revealed that these control variables did not have significant qualitative and quantitative effects on the model outcomes. Table 1 lists all input, output and control variables of the models.

Appendix D. Experimental Data Analysis

The analysis of experimental data was primarily done using multivariate regressions, which estimated the partial impact of the input variables on the output variables. In some cases, such as when examining the shape of technology trajectories, we have used visual graphical methods. In others, where we compare outcomes of the two regimes, we use standard statistical comparisons between mean values. In such cases, the nonparametric Wilcoxon Signed Rank tests are used for pairwise comparisons across all experiments. Experiments were ordered consistently when simulations have been carried out in both OS and PL, on the basis of a given combination of $(\gamma, \overline{\epsilon}, M, N)$. For comparison between the two regimes, PL outcomes were reduced to these four input variables by averaging over the results of the additional three input variables (z_j).

The OLS regressions testing the relationship between input and output variables were of the following form:

$$y = \alpha + \beta_1\gamma + \beta_2\overline{\epsilon} + \beta_3 M + \beta_4 N + \sum_j \lambda_j z_j + \theta.$$

where, y is the relevant output variable (or a transformation of it), $z_j \in \{r, \Phi, \rho\}$ are the additional input variables in the PL model, λ_j the corresponding coefficients, θ is the regression error, and α, β_i are the constant term and the coefficient of regression of the main input variables. This regression equation does not represent a "true" relationship between the variables, given the non-linear interactions which are the essence of a complex agent based model. However, it does provide us with a measure of how responsive the system (or parts of the system) are to changes in the underlying parameters of the model, i.e. the partial correlation between input and output variables. Note that no causal inference is being made as a result, as causality operates through the complex interactions within the simulations. The results simply state the marginal impact of changing an input variable on the outputs.

Note that we use the data for the firm agent identified as 1 in the simulations for all firm specific outcomes. This does not create any bias as each experiment incorporated multiple runs and in every case, the firms were allocated an identifier randomly by Netlogo. Hence choosing any one firm consistently across repetitions of the same experiment is equivalent to choosing a random firm in each repetition. Additionally, OS provided each firm agent with two possible strategies – choose a competitor's technology (s^1) or choose own technology (s^2). On the other hand, PL allowed three possible strategies – licence competitor's technology (s^1), copy competitor's technology (s^2) and use own (s^3). Hence, the probability of using own technology in period t for OS is $\sigma^2(t)$, and for PL is $\sigma^3(t)$ (while the rest of the alternatives correspond to one or more ways of using a competitor's technology under each regime).

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