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Innovation eco-systems and the Risk-Reward Nexus: an evolutionary account

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Abstract The aim of this report is to study the relation between finance, innovation and inequality, focusing on the role of different actors in financing innovation and their share in the profit that results from an average of successful and unsuccessful projects. Based on a set of metrics for the distribution of risk taking and profit sharing in the innovation process, this report compares different types of innovation 'eco-systems' through an agent-based evolutionary simulation model. On one extreme, innovation investment relies (almost) exclusively on private finance. On the other, innovation relies (mainly) on public investment. By devising alternative parametric scenarios we analyse outcomes under alternative levels of risk, sketching stylised dynamics related to narratives behind actual innovation processes.

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1 Introduction

Evolutionary accounts of the innovation process have argued that systems of innovation facilitate the diffusion of new knowledge throughout the economy (Freeman, 1987). Systems of innovation (sectoral, regional, national) require the presence of dynamic links between their different actors (firms, financial institutions, research/education, public sector funds, intermediary institutions), as well as horizontal links within organizations and institutions (Freeman, 1995).

The role that the public sector and private firms play in a complex and competitive technological *landscape* has been only partially explored. Innovation policies may under-perform if agents play the wrong role in the wrong part of the technological landscape (in time and space). For example, recent evidence from the OECD suggests that private venture capitalists take the lead in investing in emerging *technologies*, with respect to government funded venture capitalists (Breschi et al., 2018),[1] whereas public investment leads the Research of R&D in the early and most risky stage of new *industries* (Comins, 2015). For instance, in biotechnology, nanotechnology and telecommunications, the private financing of innovation arrived two decades after the most important investments were made by public sector funds.

In hindsight, history shows that those areas of the risk landscape (within sectors at any point in time, or at the start of new sectors) that are defined by high capital intensity and high technological and market risk have required great amounts of public sector funding (of different types), as well as public sector vision and leadership to get them off the ground (Mazzucato, 2013).

A more comprehensive understanding of the risks associated to developing new technologies gives credit to the role of the public sector in innovative activities. Central to this understanding is the need to better identify how the division of *innovative labour* maps into a public-private division of rewards. A critical point is defining the relation between those who bear risk in contributing to the innovation process and those who appropriate rewards from it. Doing so makes it immediately logical for there to be a more collective distribution of the rewards, proportional to the risks taken.

The present report aims to explore the relationship between innovation performance and distributional outcomes by comparing different types of innovation 'eco-systems', defined by the asymmetric public/private role in financing

[1]Such as drones, virtual reality, artificial intelligence, apps, 3D printing, blockchain, and cloud computing

innovation and the associated complexity of the new technology introduced into the economy.

We build on Lazonick and Mazzucato (2013), who introduce a Risk-Reward Nexus framework to study the relationship between the extent of risk taking and profit sharing across different actors throughout the innovation chain. And we extend the agent-based simulation model in Wirkierman et al. (2018), which advances a set of metrics to quantify key aspects of the Risk-Reward Nexus.

After this brief introduction, the rest of the report is organised as follows. Section 2 motivates the use of the notion 'innovation eco-system', whereas section 3 discusses some general features of our simulation model. Then, section 4 defines the innovation 'eco-systems' as seen through the lens of the model, and relates them to narratives of actual innovation processes. In section 5 we present results of simulation exercises and discuss the emerging patterns. Finally, section 6 concludes.

2 Innovation eco-systems

The literature on public support to innovation has focused mainly on innovation policies based on R&D subsidies, and their role in crowding out or augmenting firms' innovative activities. Results are mixed (Dimos and Pugh, 2016; Petrin, 2018), with some studies finding that public intervention does not increase firms' investment in R&D (Radicic and Pugh, 2016), and others that find a significant additionality (Dechezleprêtre et al., 2016).

In this report we focus on directed public intervention in research, and the role of public sector in fostering innovation, through its impact on the market, and on firms' capabilities to explore complex technological landscapes.

Within the context of our analysis, we consider an innovation 'eco-system' as the (multi-layered) interconnected array of agents and institutional mechanisms behind processes of technological and market competition for the development of a new technology through innovation.[2]

By referring to innovation systems as 'eco-systems', we aim to explicitly distinguish the *symbiotic* from the *parasitic* nature of the relationship between public and private agents throughout the innovation chain, in analogy with the motivations and implications of such terms within an ecological framework.

In a symbiotic relationship, each agent provides for the other the conditions

[2]The term innovation 'eco-system' is not universally accepted nor unambiguously defined by scholars within the Innovation Studies tradition. See Oh et al. (2016) for a critical view.

required for their mutual continued existence, the ultimate implication of it being that agents depend on each other equally. Instead, in a parasitic relationship, an agent takes advantage of another agent (of a different type) feeding from it, resulting in a deep asymmetry that weakens the latter, ultimately threatening their mutual existence.

How can we be sure that the innovation eco-system is one that results in a symbiotic relationship between the public and private sector rather than a parasitic one? That is, will increased investments by the State in the innovation eco-system cause the private sector to invest less, and use its retained earnings to fund short-term profits, or more, in R&D expenditure?

Usually a question like this might be discussed in terms of conflicting views about the 'crowding-out' hypothesis: whether State investment uses up savings that could have been used by the private sector for its own investment plans (Friedman, 1979), as opposed to the idea that the economy is hardly ever under a situation of full resource utilisation in which the trade-off between public and private investment holds. As mentioned, results from the literature on R&D subsidies are mixed (Dimos and Pugh, 2016; Petrin, 2018), whereas results from the venture capital literature suggest that there is little evidence of crowding out (Breschi et al., 2018).

However, by focusing exclusively on discussing the crowding-out hypothesis, we insufficiently acknowledge the fact that the State invests in areas that the private sector would not invest *even if* it had the resources. Firm-level studies have shown that what drives entry behaviour into industries are not existing profits in that sector but projected technological and market opportunities (Dosi et al., 1997). And such opportunities may be linked to the amount of State investment in research in those areas.

Policymakers may not be ambitious enough to demand that such support be part of a more collaborative effort in which the private sector also steps up to the challenge. And in this way we risk allowing a *symbiotic* innovation system, in which the State and private sector mutually benefit, to transform into a *parasitic* one in which the private sector is able to leach benefits from a State that it simultaneously refuses to finance.

In this report we discuss three varieties of innovation eco-systems, which crucially differ in the public/private distribution of risk taking and profit sharing across the innovation chain. We codify these differences into the evolutionary agent-based simulation model introduced in Wirkierman et al. (2018), adapting it to cope with alternative institutional mechanisms defining asymmetric roles for public/private agents in the financing of innovation. The trajectories obtained from the model represent a stylised (and approximate) depiction of (selected features of) actual processes of technological and market competition in the development of a new technology.

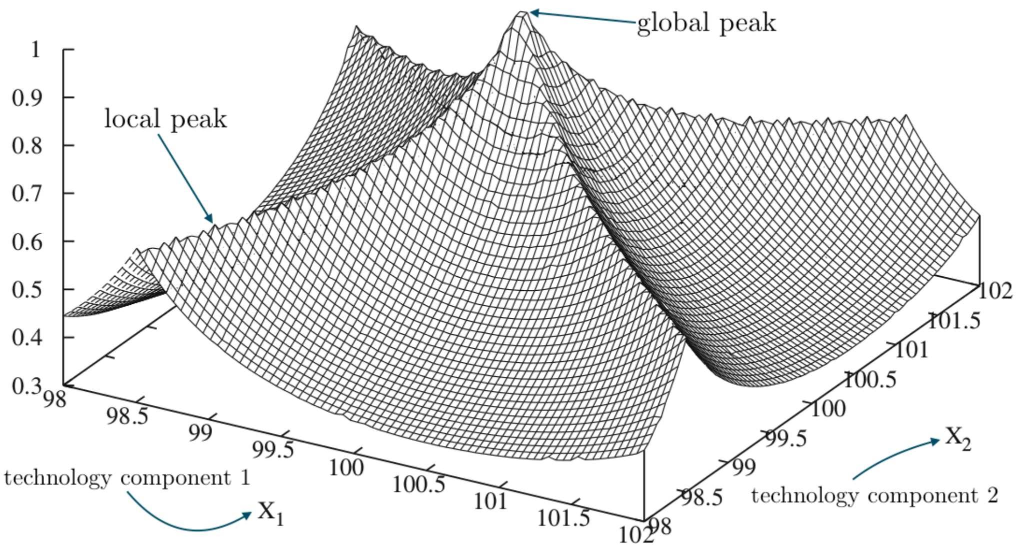
3 The model

To study the relationship between an innovation process and the distribution of risks and rewards – under alternative 'eco-systems' – we use an agent-based simulation model of technological competition. Across configurations, there are two agent types: A (public sector) and B (private firms). There is one instance of type-A and $n_B(t)$ instances of type-B, indexed as $i = 1, 2, \ldots, n_B(t)$ for each time period t.[3] In this section, we only present selected equations portraying key aspects of the model. Full details of its specification can be found in Wirkierman et al. (2018).

3.1 Performance: Technology, demand and competition

In our framework, technology is represented by the fitness landscape of a pseudo-NK model (Valente, 2014): a multi-peaked surface with a unique *global* peak, which represents the dominant design (Klepper, 1996) of a new technology (see Figure 1, for an example).

Figure 1: Example of two-dimensional fitness landscape (adapted from Valente, 2014, p. 117)



[3]The number of private firms $n_B(t)$ changes through time.

Each dimension in the landscape represents a component of a new technology being introduced into the economy. Technology components may be mutually dependent on each other. Within this framework, the complexity of the innovation process consists in the degree of connection between each pair of technology components. For any given couple of dimensions j and k, a_{jk} represents the degree to which component j depends on component k, and this degree ranges from 0 (complete independence) to 1 (maximum interdependence). A high degree of interdependence between dimensions j and k means that a movement along dimension j, for different values of k, changes the impact of dimension j on fitness from negative (positive) to positive (negative).[4]

Every agent (the public sector and each private firm) explores the landscape at each time-period, and each position (e.g. (x_1, x_2) in Figure 1) has a fitness score associated to it (the value on the vertical axis associated to (x_1, x_2) in Figure 1). This fitness score $\alpha^i(t)$ represents the product quality reached by the agent at time t.

Given the 'rugged' nature of the landscape, throughout this gradual and local search process agents risk facing a *lock-in* problem: moving to a contiguous landscape position in every dimension may not lead to any increase in fitness at a *local* level (e.g. the local peak in Figure 1). If this is the case, the flow of resources used to explore the landscape does not lead to any improvement in product quality.

This new technology is used in a new industry producing a final product. We assume that demand increases with the quality of the product. The size of the market, i.e. total final demand $F(t)$, is functionally related to average product quality by a logistic curve (reflecting non-linearity and saturation effects):[5]

$$F(t) = \frac{100}{1 + e^{-\phi_1(\phi_2\overline{\alpha}(t) - \phi_3)}} \tag{1}$$

where aggregate product quality is given by the average (across all agents) contribution to fitness of the technology landscape, $\overline{\alpha}(t)$.

Final demand addressed to each firm $f^i(t)$ is a share $\theta^i(t)$ in total final

[4] In Figure 1, this means that the effect on fitness of a movement along the X_1 axis can change sign depending on the contingent value of the X_2 axis, and vice-versa.

[5] Parameters (ϕ_1, ϕ_2, ϕ_3) govern the shape of the curve. In our implementation, $(\phi_1, \phi_2, \phi_3) = (0.35, 50, 35)$.

demand $F(t)$:

$$f^i(t) = \theta^i(t)F(t), \quad \text{such that} \quad \sum_{i=1}^{n_B(t)} f^i(t) = F(t) \tag{2}$$

where $\theta^i(t)$ is the market share of the i-th. firm at time t.

The evolution of market shares $\theta^i(t)$ is determined by a replicator equation (Metcalfe, 1998), which crucially depends on the extent to which the product quality of a firm, $\alpha^i(t)$, is above/below the (lagged) average for type-B agents, $\overline{\alpha}_B(t-1)$:

$$\theta^i(t) = \theta^i(t-1)\left(1 + \chi\frac{\alpha^i(t) - \overline{\alpha}^B(t-1)}{\overline{\alpha}^B(t-1)}\right) \tag{3}$$

where χ is the intensity of replicator dynamics, $\alpha^i(t)$ is the product quality of the product of the i-th. firm at time t, and $\overline{\alpha}_B(t-1)$ is the (lagged) average product quality across $n_B(t-1)$ firms at time $t-1$.

Besides the dynamics implied by (3), the model has three mechanisms that foster intense market competition:[6]

1. The initial position on the technological landscape of an entrant is drawn from a uniform distribution continuously changing, with an upper limit given by the current position of the incumbent with highest fitness (which includes the public sector) plus a *stochastic* factor;[7]

2. Entrants rip a slice of the market share of the *biggest* incumbent. Initially, the entrant is appealing due to the sense of novelty it entails. A share of consumers is not aware of the quality difference between the leading incumbent and the entrant until they try the latter's product;

3. Incumbents with particularly high market shares reduce their re-investment in R&D out of profits, therefore slowing down landscape exploration in relation to more dynamic entrants.

In terms of entry and exit rules, new firms enter landscape exploration and production at a constant rate. As an exit rule, if the firm's market share falls

[6] Analytical details may be found in Wirkierman et al. (2018, pp. 9-10).

[7] This implies that entrants are more likely to lag behind the incumbents (including the state), and will need to invest in R&D to catch-up and leapfrog. Nut in exceptional cases new firms may enter with a slightly higher fitness than incumbents. This is because, technology may not be easily imitated, and a period of learning is required from the investment, to be able to advance.

below a given minimum threshold, it exits the market (Marsili, 2001). To monitor market concentration in the industry at each time period, the Herfindahl Index is computed:

$$H(t) = \sum_{i=1}^{n_B(t)} \theta^i(t)^2 \tag{4}$$

Finally, to quantify the resilience of firms operating in the market, we compute a *failure rate*, given by the number of firms that lasted for, at most, two periods (before exiting the industry) over the total number of firms that *ever entered* the industry.

3.2 Inequality: the Risk-Reward Nexus

So far, only aspects related to technological and market competition have been explored. We now turn to income relations, i.e. distributive aspects. Final demand equals the balance of primary income in this simplified economy, which is divided into profits $\Pi^B(t)$, wages $W(t)$ and the government surplus $\pi^A(t)$:

$$F(t) = W(t) + \Pi^B(t) + \pi^A(t) \tag{5}$$

We assume that R&D investment from both the public sector and private firms consists in labour costs, i.e. wages paid to specialised R&D workers who perform research and applied development of new products.[8] Formally, we have:

$$W(t) = RD^A(t) + \sum_{i=1}^{n_B(t)} RD^i(t) \tag{6}$$

where $RD^A(t)$ is public investment in R&D and $RD^i(t)$ is firm i investment in R&D.

The value created within each firm by means of quality improvements results in income generation when profits $\pi^i(t)$ are realised through sales $f^i(t)$, net of R&D expenditure for technological exploration $RD^i(t)$, taxes on revenues $\tau f^i(t)$, the payment to the public sector of a license to access the new technology $c^i_A(t)$ or the receipt of a grant $h^i_A(t)$ to explore the fitness landscape and further

[8] In the US, the share of labour costs in total intramural R&D spending by the sector of business enterprises has risen from 46% (average 1981-1985) to 66% (average 2009-2013), source: OECD Dataset on Gross Domestic Expenditure on R&D by sector of performance and type of cost.

improve the final product:

$$\pi^i(t) = (1-\tau)f^i(t) + h^i_A(t) - RD^i(t) - c^i_A(t) \tag{7}$$

The public sector spends $RD^A(t)$ in R&D to explore the technology landscape, supports technological exploration of some private firms by providing grants $h^i_A(t)$, receives income from the license for operating the new technology that some firms pay $c^i_A(t)$, and collects taxes from firms' sales. As a result, government surplus $\pi^A(t)$ is given by:

$$\pi^A(t) = \sum_{i=1}^{n_B(t)} \tau f^i(t) + \sum_{i=1}^{n_B^{Lic}(t)} c^i_A(t) - \sum_{i=1}^{n_B^{Gr}(t)} h^i_A(t) - RD^A(t) \tag{8}$$

where $n_B^{Lic}(t)$ is the number of firms that pay the license cost to the public sector and $n_B^{Gr}(t)$ is the number of firms that receive a grant, during period t.

Adopting the measure of risk taking and profit sharing introduced in Wirkierman et al. (2018), the Risk-Reward Nexus of agent i is given by:

$$RRN^i(T^i) = \frac{\text{Reward}}{\text{Risk}} = \frac{\mu^i(T^i)}{\sigma^i(T^i)} = \frac{1/T^i \sum_{t=0}^{T^i} \pi^i(t)}{(1-\alpha^i(0))(\alpha^i(T^i) - \alpha^i(0))} \tag{9}$$

where $\pi^i(t)$ are the profits of the agent at time t, $\alpha^i(t)$ is landscape fitness score at time t, and T^i is the exit time of agent i from the market.

In (9), while the meaning of the numerator is self-explanatory (profits or government surplus represent a time-averaged measure of reward), the measure of risk in the denominator is the product of: (i) the initial distance to the dominant design $(1-\alpha^i(0))$ and (ii) the length (in terms of fitness improvements) of the path explored $(\alpha^i(T^i) - \alpha^i(0))$. Intuitively, agents that invested early in the technology will begin from a distant position to the dominant design (low $\alpha^i(0)$), implying a higher risk. Moreover, conditional on its initial position, the more an agent has explored the more risk it has faced throughout the process (larger $(\alpha^i(T^i) - \alpha^i(0))$).

The process of technological and market competition embedded in the model – together with the institutional mechanisms of the innovation eco-system – may generate (in different ways) an *imbalance* between risks (represented by the distance from the dominant design of the new technology and the length of landscape explored) and rewards (represented by profitability). The measure of Risk-Reward Nexus in (9) allows us to quantify the extent of this imbalance throughout alternative scenarios of the model.

4 Innovation eco-systems within the simulation model: gestation, licensing and grants

In a nutshell, the intuition of the model introduced in section 3 runs as follows. After being allocated an initial random position on the technological landscape, agents locally explore the landscape to improve the fitness score, which represents the quality of the final product. The size of the market (i.e. industry demand) increases with *average* product quality, whereas product quality differentials determine the change in market shares. A higher market share implies higher revenues, which drive R&D investment to execute further steps in the exploration of the technology landscape, obtaining a new fitness score, associated to a better product quality: a new loop has begun. This cumulative process repeats itself, and may lead to virtuous or vicious circles, both in terms of innovation diffusion (i.e. market size) and inequality (i.e. imbalance between risks and rewards).

In this context, we consider three different innovation eco-systems, labelled: (i) Gestation, (ii) Licensing and (iii) Grants.

4.1 Gestation

The technology life-cycle associated to the final product of an industry consists of three stages: gestation, vital life and maturity. The gestation phase of the life-cycle is the riskiest: due to the low product quality and small market size, private firms may have little incentives to start exploring the technology landscape.

Thus, we assume that exploration in this initial phase of an industry is triggered by the public sector. Only after the public agent reaches a fitness such that the market size attains a minimum threshold, private firms start to explore the technology landscape. In this way, R&D performed by the public sector during the gestation period fuels knowledge accumulation that will be later exploited by private firms.

Under the 'gestation' innovation eco-system, the knowledge generated by the State at the gestation stage of the life-cycle is available to *all* private firms, once they start exploring the landscape and producing the final product. But, at that point, it is *only* up to private agents to increase *average* product quality in the industry, leading to a market expansion. The public sector no longer actively engages in R&D expenditure (and landscape exploration).[9] This institutional arrangement has, at least, two implications. First, the initial effort made by the public agent might not be fully compensated by taxation at more advanced stages of the technology life-cycle. Second, once market competition is in place, the knowledge available to a late entrant might be rather limited in comparison to the distance from the dominant design reached by leading incumbents.

In terms of equations (7) and (8) of the model, this eco-system implies that:

$$\pi^i(t) = (1-\tau)f^i(t) - RD^i(t)$$
$$\pi^A(t) = \sum_{i=1}^{n_B(t)} \tau f^i(t) - RD^A(t)$$

i.e. the only public/private redistribution mechanism is taxation of firms' revenues.

In the simulation exercises of section 5, this eco-system is used as a *benchmark*: after the gestation stage of the technology life-cycle, innovation investment relies exclusively on private finance. Instead, in the two alternative innovation eco-systems discussed below, there is a more active role of the public sector throughout the innovation chain.

4.2 Licensing

A first alternative to the 'gestation' eco-system is represented by the 'licensing' innovation eco-system. Under this institutional arrangement, the public sector directly invests in R&D *throughout* the innovation chain, charging a license fee to firms who want to access their accumulated technological knowledge. Private firms *may* take advantage of the privileged landscape position reached by the public sector, acquiring the license to operate the new technology and obtaining a relatively high fitness score in the technology landscape, product quality and market share, since entry, thus accessing innovation surplus profits. These profits are channeled as dividends, whereas investment in R&D contributes to the development of skills of R&D workers, increasing wages.

Firms that pay the license fee to access accumulated knowledge by the public sector not only have an *initial* advantageous landscape position, but also in the

[9] Recalling that we refer to the specific technology used to produce the final product of the industry considered. It is assumed that the public sector moves towards a new technology landscape to start a different exploration process.

event of a technological *lock-in* (i.e. when by moving locally in any direction of the landscape they cannot increase their fitness) a fee payment allows them to move to the *current* position of the public sector.[10] Given that the public sector in this eco-system is actively engaged – throughout the life-cycle – in direct R&D expenditure and landscape exploration to close the gap with respect to the dominant design, by paying the license fee some private firms can make a *non-local* jump, exiting the lock-in situation and rekindling exploration from a different area in the landscape. This allows them to avoid stagnation in their product quality which may lead to decreases in their market share when other firms find a more promising path to technological improvement.

Thus, under the 'licensing' eco-system, if a private firm that does not pay the license to the public sector faces a lock-in, its R&D expenditure will produce no further increases in product quality, and it will probably be overtaken by firms that that pay a license, or do not fall in lock-ins (e.g. entrants that have a license advantage to access the current state of the new technology).

In terms of equations (7) and (8) of the model, this eco-system implies that:

$$\pi^i(t) = (1-\tau)f^i(t) - RD^i(t) - c_A^i(t)$$
$$\pi^A(t) = \sum_{i=1}^{n_B(t)} \tau f^i(t) + \sum_{i=1}^{n_B^{Lic}(t)} c_A^i(t) - RD^A(t)$$

i.e. there are two public/private redistribution mechanisms: taxation of firms' revenues ($\tau f^i(t)$) and license fees to access the current state of accumulated knowledge by the public sector ($c_A^i(t)$).[11]

4.3 Grants

A third alternative is represented by the 'grants' innovation eco-system. Under this institutional arrangement, the public sector directly invests in R&D *only* during the gestation phase of the life-cycle. Once the State reaches a fitness score such that the market size attains a minimum threshold, private firms start to explore the technology landscape. Randomly, entrants might be selected to participate in a grant scheme offered by the public sector. If this is the case,

[10] We assume that private firms cannot make 'jumps' across the landscape, and have therefore a higher propensity to lock-in in local optima. Instead, the public actor can invest large amounts of resources in risky research, therefore moving to completely unknown part of the landscape, making 'jumps'.

[11] Analytical details on the determination of the license fee paid by private firms may be found in Wirkierman et al. (2018, pp. 12-3).

knowledge previously accumulated by the public sector is rendered available to grantees, who are also financially supported by the State to expand landscape exploration further.

Differently from the 'licensing' eco-system (and similarly to the 'gestation' eco-system), the public sector is only engaged in direct R&D expenditure at the early stage of the technology life-cycle. Then, it is up to private firms to achieve higher product quality by progressively closing the gap with the dominant design. However, differently from the 'gestation' eco-system (and similarly to the 'licensing' eco-system), the public sector continues to support private firms after the gestation phase: the State explores the technology landscape *indirectly*, by allocating grants to private agents.

The total expenditure in R&D by the public sector is distributed between direct exploration (during the gestation phase) and grants (after gestation). As an allocation rule, grants provided by the public sector are distributed *inversely* proportional to the firm's market share. In principle, such an allocation rule encourages a catching-up process for entrants. However, the public sector finances its grants by means of previously accumulated surplus. Thus, if a higher diversification of grant allocation slows down market size expansion (due to the multiplicity of decentralised efforts to explore the technology landscape), revenue taxation may be stagnant and, even though grants would be more equally distributed, the absolute amount of resources perceived by some grantees may decline. These are the nuances of a *steady* pattern of grant expenditure with a dynamic allocation rule.

In terms of equations (7) and (8) of the model, this eco-system implies that:

$$\pi^i(t) = (1-\tau)f^i(t) + h^i_A(t) - RD^i(t)$$
$$\pi^A(t) = \sum_{i=1}^{n_B(t)} \tau f^i(t) - \sum_{i=1}^{n_B^{Gr}(t)} h^i_A(t) - RD^A(t)$$

i.e. there are two public/private redistribution mechanisms: taxation of firms' revenues ($\tau f^i(t)$) and grants allocated by the public sector to private firms in order to explore the technology landscape ($h^i_A(t)$).

4.4 Innovation eco-systems as narratives behind actual innovation processes

The institutional arrangements defining each eco-system previously described are an apparent simplification of the complexity behind innovation episodes throughout history. This notwithstanding, the stylised eco-systems within the simulation model have been conceived with reference to some aspects of actual innovation processes.

The pharmaceutical industry is a first interesting case in point. Large pharma, small biotech, universities and government labs are all parts of the eco-system. Government labs and government-backed universities focus on the research responsible for producing the most radical new drugs. Private pharma has focused more on 'me too' drugs (slight variations of existing ones) and the development (including clinical trials) and marketing side of the business.

It is an industry in which scientific knowledge plays a central role and is only *partly* appropriable. Part of the knowledge that is used to produce new drugs is generated by and/or based on publicly funded scientific research, and in principle freely accessible. Thus, by accessing publicly funded research done during the gestation stages of drug development, pharmaceutical companies are at least partly "subsidised" when they step into the process of technological exploration. For example, the development of the biotech industry in the US is a direct product of the key role of the government in leading the development of the *knowledge base* that has provided firm success and the overall growth of the industry (Mazzucato, 2013). These considerations suggest that the 'gestation' eco-system might capture some features of the technology life-cycles associated to pharmaceutical innovation.

However, we must be wary of the fact that the pharmaceutical industry has experienced radical transformations in the last decades, since the end of its 'golden age' (form the second post-war period up to the 1980s). Health systems at the height of the welfare state era implied sustained public financing of health-related research, exploited by private actors (Orsenigo et al., 2006). Within this context, the emerging dominance of "big pharma" changed innovation models. Many large pharma companies downsized – or closed altogether – R&D labs moving towards an 'open' model of innovation that outsources – to small biotech firms or public labs – most of their research-intensive tasks (Gambardella, 1995).

Features of the 'licensing' eco-system may be connected to the development of some of Apple's iPhone components (Mazzucato, 2013, ch. 5).[12] One of the key recent features in iPhone models is the virtual personal assistant known as SIRI.[13]

[12]Within this context, a 'license fee' is *broadly* intended as a generic label for an institutional device that allows the public sector to commercialise a technology it has developed.

[13]SIRI is an artificial intelligence platform combining natural language processing, statistical learning and a

As with many other key technological features in Apple's iOS products, SIRI has its roots in federal funding and research. In 2000, under request of the US Defense Advanced Research Projects Agency (DARPA), the Stanford Research Institute (SRI) was put in charge of coordinating the 'Cognitive Assistant that Learns and Organizes' (CALO) project which included 20 universities all over the US collaborating to develop the necessary technology base. When the iPhone was launched in 2007, SRI recognised the opportunity for CALO as a smartphone application and then *commercialised* the technology by forming 'SIRI' as a venture-backed start-up in the same year. In 2010, SIRI was acquired by Apple.

Finally, it may be argued that the development of Photovoltaic (PV, hereinafter) solar panels in the US has some features of the 'grants' innovation eco-system. The first major opportunities for solar PV technology were created by the United States Department of Defense (DoD) and the US National Aeronautics and Space Administration (NASA), which purchased solar cells made by the US-based Hoffman Electronics Corporation to power space satellites. Currently, there are several modern governmental initiatives helping to establish leading solar PV firms, but it is interesting to trace back the origin of many innovative emerging firms in the US that managed to develop state-of-the-art technologies.

We consider four examples of industry firms (First Solar, Solyndra, Sunpower, Evergreen) with apparent public support to the private exploration of the technology landscape, following the gestation phase of the solar PV panels life-cycle.

First Solar's patents have 'extensive links' to prior US Department of Energy (DoE) research (Ruegg and Thomas, 2011, p. 4-11), and early development of First Solar's leading technology was a result of close collaboration with State-funded solar research facilities, university scientists and the US National Renewable Energy Laboratory (NREL). Solyndra developed innovative technology with state and federal support, building on previous national research conducted on thin-film solar cells. The success of SunPower, a leading manufacturer of high performance solar PV panels, ties back to DoE research patents, in this case related to solar PV shingles, module frames and shingle systems (Ruegg and Thomas, 2011). In fact, SunPower had early R&D support from the DoE and the Electric Power Research Institute (EPRI) while developing technology at Stanford University. Finally, Evergreen Solar grew with the aid

family of web search algorithms.

of the government, attracting USD 60 mln. in state subsidies.

The proposed analogies between innovation eco-systems within the simulation model ('gestation', 'licensing' and 'grants') and actual processes of technological change (within the pharmaceutical industry, Apple's iPhone components and solar PV panels, respectively) represent an effort to bridge the theoretical account of industry dynamics captured by a Risk-Reward Nexus framework and concrete examples of innovation trajectories. As such, these analogies cannot (and are not intended to) mirror historical episodes comprehensively. They simply represent a preliminary device to appraise and map simulation results to categories and orders of magnitude found in actual industries.

5 Simulation results

The model discussed in sections 3 and 4 cannot be solved analytically due to the non-linearities implicit in its specification. In view of this, a discrete-time simulation platform has been used to codify and implement it.[14] Parametric configurations for three alternative innovation eco-systems subject to different technological complexity have been devised, performing extensive randomizations for each of them, in order to control for across-simulation variability.

We report below across-run averages over 50 replications for each scenario considered and within-scenario correlation matrices, in order to uncover both statistical first moments and significant co-movements.

In what follows, after a brief characterisation of alternative scenarios and metrics computed, we (statistically) compare simulation outcomes and interrelationships between innovation performance and inequality across scenarios.

5.1 Alternative scenarios

We analyse six scenarios that depend on two dimensions: (i) the innovation eco-system and (ii) the complexity of the new technology introduced (medium vs. high complexity) – the higher the complexity, the more difficult it is to improve the quality of the product and the more likely it is to fall in a lock-in, for a given investment in R&D; returns to investment are consequently lower.

In particular, scenarios are defined as follows:

1. **Gestation** public R&D scheme and **medium** tech-complexity:

[14] All simulations have been programmed using the Laboratory for Simulation Development (LSD). For more information see `https://github.com/marcov64/Lsd`.

(*benchmark* scenario)
The public sector is involved in the process of technological exploration by directly investing in R&D *only* at early stages of the innovation chain (i.e. gestation), whereas it is *only* up to private firms to further improve product quality, in a context in which the intensity of interdependence between components of the new technology (i.e. dimensions of the fitness landscape) is of medium complexity. Within this eco-system, once demand is sufficient for private firms to enter the industry, the public sector lets innovation development be driven by the private firms.

2. **Licensing** R&D scheme and **medium** tech-complexity:
The public sector is involved in the process of technological exploration by directly investing in R&D *throughout* the innovation chain, and private firms pay a license fee to access the accumulated knowledge stock and the position of the public investor on the technological landscape, in a context of medium complexity of the new technology. Within this eco-system, once demand is sufficient for private firms to enter the industry, the public sector lets them access the accumulated knowledge stock, and their position on the technological landscape, by paying a license fee. Those who do, start technological exploration from a relatively advantageous position.

3. **Grants** R&D scheme and **medium** tech-complexity:
The public sector is involved in the process of technological exploration by directly investing in R&D *only* at early stages of the innovation chain (i.e. gestation), supporting private firms through grants to further develop the product's quality, in a context of medium complexity of the new technology. Within this eco-system, once demand is sufficient for private firms to enter the industry, the public sector supports further innovation development by allocating grants for technological exploration to private firms.

4. **Gestation** public R&D, **high** tech-complexity:
Public-private roles are the same as those under eco-system 1, but in a context in which the complexity of the new technology is *high* (the contribution to fitness of movements in one landscape direction heavily depends on the relative position in other dimensions of the landscape).

5. **Licensing** R&D scheme, **high** tech-complexity:

Public-private roles are the same as those under eco-system 2, in a context of high complexity of the new technology.

6. **Grants** R&D scheme, **high** tech-complexity:
   Public-private roles are the same as those under eco-system 3, in a context of high complexity of the new technology.

While section 4 has explained in detail the difference between innovation eco-systems, the differing complexity of the new technology (medium/high) intends to capture alternative levels of risk of the environment in which agents operate. In scenarios of *medium* technological complexity *lock-in* episodes are less frequent due to a lower 'ruggedness' of the technology landscape. This reduces the level of aggregate risk for all agents exploring the technological landscape, all things being equal. On the contrary, in scenarios of *high* technological complexity, the likelihood of facing lock-in and halting technological advances is higher, increasing aggregate risk, *cœteris paribus*. In fact, firms who cannot make a *jump* to an entirely different area of the technological landscape, will eventually be overtaken by entrants who take pathways leading to higher product quality, and exit the market.

Table 1 reports a summary of the scenarios just described, to ease understanding and for later reference throughout the analysis of results.

Table 1: Simulation scenarios

Tech-Complexity	Eco-system	Scenario
Medium	Gestation	1
	Licensing	2
	Grants	3
High	Gestation	4
	Licensing	5
	Grants	6

Table 2 reports model parameters that appear in equations (1)-(9).[15]

From Table 2 we see that the complexity of the technology stems from the value of parameter a_{ij}. The higher a_{ij}, the higher is the dependence of each technological component on the position in *other* components, to assess the

[15] A more complete parameter list can be found in Wirkierman et al. (2018, p. 21).

Table 2: Across-scenarios and scenario-specific parameters

Parameter	Description	Tech-Complexity	Range	Value
	Complexity of the technology: pseudo-NK landscape			
N	Landscape dimensions	Both	≥ 2	2
a_{ij}	Intensity of interaction	Medium	$[0,1]$	0.35
		High	$[0,1]$	0.60
	Competition regime			
χ	Intensity of replicator dynamics	Both	$[0,1]$	0.50
	Public policy			
τ	Tax rate on sales	Both	$[0,1]$	0.10

Simulation steps = 150; entrants per entry-period = 2; entry interval = 4.

relative contribution to fitness. A higher value of a_{ij} increases the *ruggedness* of the technology landscape. In our scenarios with medium complexity of the technology (scenarios 1, 2, 3), $a_{ij} = a = 0.35$, whereas in those with high complexity (scenarios 4, 5, 6), $a_{ij} = a = 0.65$.

5.2 Metrics

In order to compare alternative scenarios we compute a set of metrics for each run of the simulation model, enumerated in Table 3.

Table 3: Simulation metrics: specification of indicators computed

(Time period T represents the simulation step in which the dominant design has been reached by one of the private firms)

		Indicator	Formula	Reference Eqs.
Industry Structure and Innovation Performance	1.1	Final Demand at T	$F(T)$	(1)
	1.2	Aggregate Private Risk at T	$a/\overline{\alpha}^B(T)$	(3)
	1.3	Herfindahl Index at T	$\sum_{i=1}^{n_B(T)} \theta^i(T)^2$	(4)
	1.4	Failure rate at T	$n_B^{\text{fail}}(T)/n_B(T)$	—
Inequality and the Risk-Reward Nexus	2.1	Wage share in final demand	$\sum_{t=1}^{T} W(t)/\sum_{t=1}^{T} F(t)$	(5)
	2.2	RRN Private Firms (Reward/Risk)	$\overline{RRN}^B(T)$	(9)
	2.3	RRN Public Sector (Reward/Risk)	$RRN^A(T)$	(9)
	2.4	Relative RRN (private/public)	$\overline{RRN}^B(T)/RRN^A(T)$	(9)

Notes: $n_B^{\text{fail}}(t)$ represents the number of firms that lasted for two periods at most (before exiting the industry) up to time period t. Parameter a measures the strength of the dependence of one landscape dimension on the position in *other* dimensions to assess the contribution to fitness.

We compare the scenarios considering indicators regarding, crucially, two dimensions: innovation performance and inequality. In each case indicators have been computed as time-averages of accumulated variables up to time-period T and/or at the values they adopt in T. Time period T represents the simulation step in which the dominant design has been reached by one of the private firms.[16]

The first set of metrics (indicators 1.1-1.4 in Table 3) concerns innovation performance. In our model, the size of the market is given by industry's final demand $F(t)$ and, being normalised between 0 and 100, it allows to be interpreted as the percentage of adopters of the product obtained with the new technology. Thus, indicator 1.1 measures *innovation diffusion*, which is also a measure of the fitness of the technology reached by firms (or product quality).

Indicator 1.2 measures *aggregate risk* for private firms: for a given complexity of the technology (captured by parameter a), aggregate risk associated to technological exploration will be higher the lower the average fitness score collectively achieved ($\overline{\alpha}^B(T)$). The Herfindahl Index (indicator 1.3) measures the degree of market concentration associated to the process of technological competition. In relation to this, the failure rate (indicator 1.4) captures the degree of unsuccessful investment projects resulting from the collective and uncertain process of innovation.

The second set of metrics (indicators 2.1-2.4 in Table 3) concerns two dimensions of inequality: (i) the share of wages in the distribution of the net output of the industry (indicator 2.1) and (ii) the private, public and *relative* Risk-Reward Nexus (indicators 2.1-2.4).

The extent of inequality associated to investment dynamics is captured by the wage share in final demand (indicator 2.1), as it proxies the extent of value extraction: increasing dividends (and profits) slow down R&D investment and the development of skills by R&D workers.

The Risk-Reward Nexus, instead, quantifies the imbalance between the profits extracted from an innovation process by a given agent type (public/private), and the associated risks taken to finance innovation (through R&D investment to explore the technological landscape) for each agent type (public/private).

5.3 Innovation eco-systems: average features

The indicators presented in Table 3 apply to each simulation run for every alternative scenario. In order compare the scenarios summarised in Table 1, we

[16]Taking T as the end-period of our analysis is justified by the fact that the key aspects of technological and market competition are reflected in what happens up to the point when a firm reaches the dominant design. From that point onwards, it may as well happen that the public sector and private firms move on to develop another technology (exploring a new fitness landscape).

compute across-run averages over 50 replications for each of them and report these averages in Table 4.

Our interest lies in making a statistical comparison *between* eco-systems ('gestation', 'licensing' and 'grants'), *given* their environment (i.e. medium/high technological complexity). To assess whether across-run averages are statistically different we perform four Welch's unequal variances t-test and report p-values in the corresponding columns of Table 4.[17] We take the 'gestation' eco-system as our benchmark and, for each risk level, compare average results obtained for each indicator [1.1]-[2.4] in Table 3.

The table shows that aggregate private risk is mostly dependent on the environment. This is an expected result: *aggregate* risk in our model is partially determined by parameter a, which defines the complexity of the technology.[18] It also depends on the average landscape fitness value, i.e. the collective outcome of private innovative efforts in the industry. Simulation results suggest that the former dominates over the latter. This means that, in the model, changing the public/private institutional arrangement (i.e. switching to another eco-system) cannot compensate for major differences in the degree of complexity of the new technology.

Focusing on the scenarios with medium technological complexity, a more active public policy of landscape exploration (2 & 3) brings about lower concentration and failure rates, as well as higher R&D intensity, which is reflected in a higher wage share in final demand.[19]

Firms' risk is also significantly lower when grants and licenses are used – a result in line with a lower failure rate – and this is because private agents can build on a continuous public effort to either start landscape exploration from an advantageous position ('licensing') or obtain public support for additional R&D expenditure ('grants').

The public RRN is clearly lower in the 'licensing' and 'grants' eco-systems with respect to the 'gestation' one, i.e. the public sector faces a higher risk and lower reward when it intervenes beyond gestation. This is mainly due to the fact that, in this latter eco-system, the public sector is *not* actively involved (directly or indirectly) in R&D expenditure, *once* it has developed the early-stage knowledge base.

[17]The null hypothesis being that means are not statistically different.

[18]Please see section 3 for details.

[19]Recall from section 3 that, in our model, R&D investment consists in wages fostering development of skills by specialised R&D workers.

Table 4: Simulation results: average results for alternative scenarios

(across-run averages over 50 replications for each scenario, p-values correspond to Welch's unequal variances t-test comparing scenarios)

			Medium Technological Complexity					High Technological Complexity				
		Indicator	Scenario			t-test p-value		Scenario			Welch t-test	
			1	2	3	1 vs. 2	1 vs. 3	4	5	6	4 vs. 5	4 vs. 6
			Gestation	Licensing	Grants	p-value	p-value	Gestation	Licensing	Grants	p-value	p-value
Industry Structure and Innovation Performance	1.1	Final Demand at T	77.44	86.50	83.49	0.0258	0.1638	27.62	33.47	26.40	0.0000	0.2188
	1.2	Aggregate Private Risk at T	0.43	0.41	0.42	0.0680	0.6487	0.93	0.91	0.94	0.0000	0.2268
	1.3	Herfindahl Index at T	0.81	0.51	0.60	0.0000	0.0000	0.27	0.28	0.29	0.7711	0.4659
	1.4	Failure rate at T	0.66	0.53	0.56	0.0000	0.0004	0.68	0.68	0.66	0.7184	0.1459
Inequality and the Risk-Reward Nexus	2.1	Wage share in Final Demand	0.44	0.56	0.55	0.0000	0.0000	0.62	0.68	0.67	0.0000	0.0000
	2.2	RRN Private Firms (Reward/Risk)	38.46	40.59	36.22	0.8067	0.6539	68.30	115.27	84.97	0.0758	0.5599
	2.3	RRN Public Sector (Reward/Risk)	4.68	0.91	1.83	0.0000	0.0000	9.48	2.88	3.87	0.0000	0.0000
	2.4	Relative RRN (private/public)	8.49	42.85	24.57	0.0000	0.0000	7.95	45.88	21.09	0.0017	0.0121
Eco-system specific features	3.1	Share in profits of licensed firms		0.799					0.690			
	3.2	Share in taxes of grantees			0.766					0.665		

References for scenarios: **1**. gestation-publicRD, medium-tech; **2**. licensing-publicRD, medium-tech; **3**. grants-publicRD, medium-tech; **4**. gestation-publicRD, high-tech; **5**. licensing-publicRD, high-tech; **6**. grants-publicRD, medium-tech.

Consequently, the ‘gestation’ eco-system has the lowest *relative* (i.e. private/public) RRN, whereas the ‘licensing’ one has the highest value for relative RRN. Such a high relative RRN in this latter eco-system can be explained by the higher risk faced by the public sector when it takes the responsibility of sustaining continuous direct R&D expenditure to ‘technologically bail-out’ firms which get ‘locked-in’ in the process of landscape exploration.

In a nutshell, under an environment of *medium* technological complexity, the ‘gestation’ eco-system has a relatively low percentage of adopters (lowest innovation performance), highest concentration, lowest wage share and least unbalanced relative RRN. That is, lowest innovation performance, highest profit/wage gap but lowest private/public RRN imbalance.

In comparison, the ‘licensing’ eco-system has the highest percentage of adopters (highest innovation performance), lowest concentration and failure rate, highest wage share but highest imbalance between private and public RRN. That is, highest innovation performance, lowest profit/wage gap but highest private/public RRN imbalance.

Finally, the ‘grants’ eco-system has similar percentage of adopters, industry concentration and failure rates to the ‘licensing’ eco-system and an intermediate imbalance between public and private RRN. That is, high innovation performance, relatively low profit/wage gap, and an intermediate private/public RRN imbalance.

Thus, in applied terms, the setting-up of joint (public/private) research labs, financed out of public grants (i.e. associated to the ‘grants’ eco-system) – and which are active *throughout* the innovation chain – would appear as a desirable intermediate case (in terms of balancing innovation performance and relative inequalities), under an environment of medium technological complexity.

Switching to scenarios under an environment of *high* complexity of the new technology, statistical differences between eco-systems are less pronounced. The likelihood of facing technological lock-in is higher, and this element seems to dominate over the public/private institutional mechanism to push innovation forward. This notwithstanding, differences especially emerge in relation to our key synthetic indicator [2.4]: the relative RRN. In this case, *both* the *within*-environment (and between eco-systems) relative ranking and the *within*-eco-system (and between environments) orders of magnitude coincide.

This is an interesting result: our relative RRN indicator is capturing both a regularity *across* environments and a difference *between* eco-systems that no other indicator captures. For different risk levels, the private/public imbalance between rewards and risks is highest in the 'licensing' scenarios 2 and 5 (where there is an active, direct R&D involvement of the State throughout the innovation chain), lowest in the 'gestation' scenarios 1 and 4 (where the public sector is only active at an early stage of the life-cycle) and within an intermediate range in the 'grants' scenarios 3 and 6 (where the public sector is also actively involved after gestation, by indirectly supporting decentralised technological exploration of private firms).

The different role of innovation eco-systems on firms' risks and rewards is also related to the observed market structure, *more* concentrated in an environment with *lower* technological complexity. In such a regime, public intervention after the gestation phase significantly reduces market concentration: entrants face lower barriers to innovation, because they can either buy a license (starting from a landscape position closer to that of the incumbents) or receive a grant (obtaining public support to accelerate landscape exploration through increased R&D). With no public intervention, incumbents have cumulatively gained a technological advantage that new firms are rarely able to catch up with.

However, in a scenario in which the complexity of the technology is high, (i) market concentration is substantially lower, and (ii) the role of the public sector in innovation investment after gestation makes no substantial difference. The first result is explained by the fact that the high complexity makes it very unlikely for any firm to make continuous advances in product quality. The public sector, as another actor, although it has the ability to risk more and make big leaps in landscape exploration, quickly and repetitively falls into lock-in situations. Then, new entrants' technology is not so distant from that of the incumbent. The second result follows: the advantage to exploit the knowledge accumulated by the State is small, because rarely – in the span of the simulation runs analysed here – it has the opportunity to make considerable progress in such a complex landscape.

In addition to the metrics specified in Table 3, Table 4 includes two additional indicators: the share in profits of licensed firms and the share in taxes of grantees, each of them specific to the 'licensing' and 'grants' scenarios, respectively. These are useful to quantify the relative importance of those private firms that engage in the specific institutional arrangement of each eco-system.

In scenarios under the 'licensing' eco-system (2 and 4), firms that pay the license fee account for (almost) 80% (medium tech. complexity) and 70% (high tech. complexity) of industry profits; whereas in scenarios under the 'grants' eco-system, firms that have received a public grant account for 76% (medium tech. complexity) and 66% (high tech. complexity) of public revenues from taxation. Thus, it can be seen that – under each eco-system and *across* environments – firms involved in private/public institutional arrangements account for the greatest share of profits and tax revenues.

5.4 Innovation eco-systems: correlated dynamics

In this section we gain further insights on the co-movements across variables. How is innovation performance related to the Risk-Reward Nexus across eco-systems? For each scenario we gather the results of 50 simulation runs and compute the Pearson correlation coefficient for each pair of indicators [1.1]-[2.4] in Table 3.

Tables 5 and 6 report correlation coefficients for indicators of industry structure, innovation performance, inequality and RRN, when significant at least at the 10% level, for medium and high levels of technological complexity, respectively. Moreover, Figure 2 graphically depicts the relationship between selected indicator pairs across eco-systems, including a fitted simple regression model in each case.

The first result is that, while most indicators of performance and inequality are correlated in the 'gestation' eco-system (under medium technological complexity), this is not the case in the other eco-systems. Here we focus on innovation performance (proxied by final demand, which measures the percentage of adopters, i.e. market size), market concentration (proxied by the Herfindahl Index), the price/wage gap (proxied by the industry wage share), and private/public inequality, as captured by the (relative) RRN (i.e. Reward/Risk).

In an environment of high technological complexity, the relation between innovation diffusion and the wage share is negative across all eco-systems: although all R&D investment in our simplified economy accrues to wages, market size expansion through innovation generates relatively more profits than wages. When considering scenarios with medium technological complexity, this negative relation between the wage share and market size is only statistically significant in the 'gestation' eco-system, suggesting that the contribution of the public sector to the innovation process makes this distribution-growth trade-off less clear-cut: higher innovation performance can be reached *without* reducing the wage share in final demand.

Results also suggest that, in the 'gestation' eco-system, the consequences of the (tamed) replicator dynamics embedded in the model become apparent: a higher market size tends to be associated with a higher concentration index

Table 5: Correlated dynamics for alternative innovation eco-systems
(Complexity of the new technology: Medium)

(Across-run bilateral correlations statistically significant at the 10% level)

	Eco-system: Gestation								
	Indicator	[1.1]	[1.2]	[1.3]	[1.4]	[2.1]	[2.2]	[2.3]	[2.4]
[1.1]	Final Demand at T		-0.965	0.468	0.298	-0.502			-0.296
[1.2]	Aggregate Private Risk at T			-0.472	-0.283	0.461			
[1.3]	Herfindahl Index at T				0.255	-0.690	-0.665	-0.398	-0.313
[1.4]	Failure rate at T					-0.460		0.284	
[2.1]	Wage share in Final Demand						0.409		0.269
[2.2]	RRN Private Firms							0.612	0.569
[2.3]	RRN Public Sector								-0.271
[2.4]	Relative RRN								
	Eco-system: Licensing								
	Indicator	[1.1]	[1.2]	[1.3]	[1.4]	[2.1]	[2.2]	[2.3]	[2.4]
[1.1]	Final Demand at T		-0.943						
[1.2]	Aggregate Private Risk at T								
[1.3]	Herfindahl Index at T				0.380	-0.804		-0.405	
[1.4]	Failure rate at T					-0.250			
[2.1]	Wage share in Final Demand							0.483	
[2.2]	RRN Private Firms							0.437	0.933
[2.3]	RRN Public Sector								
[2.4]	Relative RRN								
	Eco-system: Grants								
	Indicator	[1.1]	[1.2]	[1.3]	[1.4]	[2.1]	[2.2]	[2.3]	[2.4]
[1.1]	Final Demand at T		-0.949						
[1.2]	Aggregate Private Risk at T					0.286		-0.244	
[1.3]	Herfindahl Index at T					-0.822			
[1.4]	Failure rate at T								
[2.1]	Wage share in Final Demand								
[2.2]	RRN Private Firms							0.327	0.449
[2.3]	RRN Public Sector								-0.466
[2.4]	Relative RRN								

and failure rate.[20]

Moving on to consider co-movements involving RRN (i.e. Reward/Risk) indicators, in a 'gestation' eco-system with medium technological complexity, innovation performance is inversely related to the relative RRN: the higher the extent to which firms are able to earn more profits relative to their risk exposure with respect to the public sector, the lower the resulting market size achieved.

[20] And given the inverse relation between market size and aggregate risk, the higher the latter, the lower the concentration index and failure rate.

Table 6: Correlated dynamics for alternative innovation eco-systems
(Complexity of the new technology: High)

(Across-run bilateral correlations statistically significant at the 10% level)

	Eco-system: Gestation Indicator	[1.1]	[1.2]	[1.3]	[1.4]	[2.1]	[2.2]	[2.3]	[2.4]
[1.1]	Final Demand at T		-0.995	0.290		-0.825			
[1.2]	Aggregate Private Risk at T			-0.277		0.825			
[1.3]	Herfindahl Index at T						0.290		0.259
[1.4]	Failure rate at T					0.555			
[2.1]	Wage share in Final Demand								-0.243
[2.2]	RRN Private Firms								0.843
[2.3]	RRN Public Sector								
[2.4]	Relative RRN								

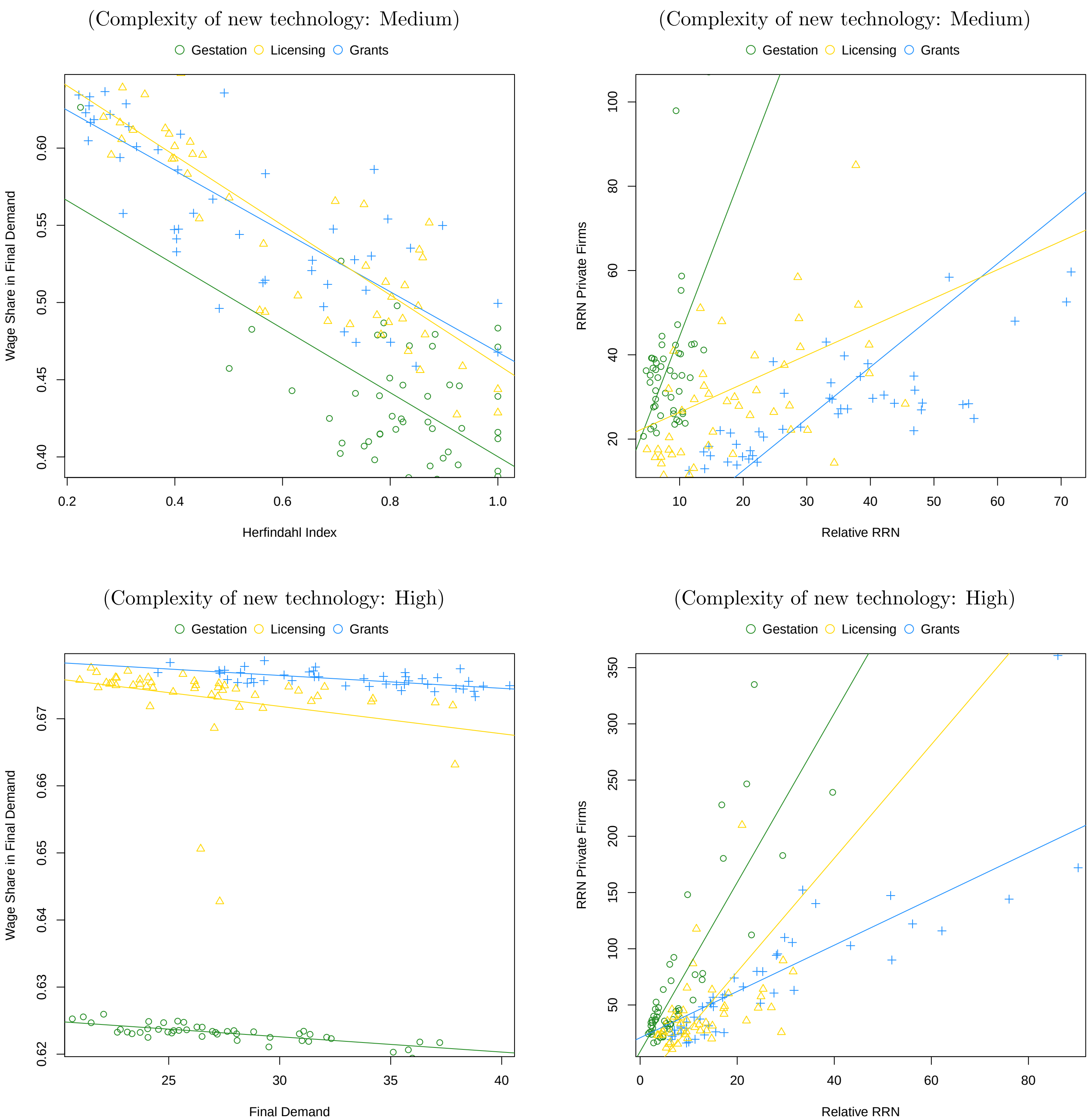
	Eco-system: Licensing Indicator	[1.1]	[1.2]	[1.3]	[1.4]	[2.1]	[2.2]	[2.3]	[2.4]
[1.1]	Final Demand at T		-0.943			-0.780			
[1.2]	Aggregate Private Risk at T					0.727			
[1.3]	Herfindahl Index at T				0.445			-0.274	
[1.4]	Failure rate at T								
[2.1]	Wage share in Final Demand								
[2.2]	RRN Private Firms								0.969
[2.3]	RRN Public Sector								-0.264
[2.4]	Relative RRN								

	Eco-system: Grants Indicator	[1.1]	[1.2]	[1.3]	[1.4]	[2.1]	[2.2]	[2.3]	[2.4]
[1.1]	Final Demand at T		-0.996			-0.308		0.326	
[1.2]	Aggregate Private Risk at T					0.322		-0.325	
[1.3]	Herfindahl Index at T							0.276	
[1.4]	Failure rate at T								
[2.1]	Wage share in Final Demand							-0.409	
[2.2]	RRN Private Firms							0.262	0.935
[2.3]	RRN Public Sector								
[2.4]	Relative RRN								

The fact that this relation is not statistically significant in the other two eco-systems suggests that public intervention breaks the link between market size and firms' ability to reap more profits while investing less.

However, robustly across scenarios, private firms' RRN is positively related to the relative (i.e. private/public) RRN. When firms' gain from relatively lower risk (for given rewards) – or relatively higher rewards (for given risks) – they are also in a position to obtain a larger share of rewards relative to their contribution, when compared to the public sector. Top and bottom right

Figure 2: Innovation Performance and Inequality *between* eco-systems



panels of Figure 2, plot this relation for both environments of technological complexity. It may be seen that, under the 'grants' eco-system, firms are able to increase (decrease) the relative RRN (obtain more rewards than the public investor, for a given risk) with a smaller increase (decrease) in private RRN (increase in rewards with respect to risk). In other eco-systems, high relative

RRN must be accompanied by substantially higher private reward or lower risk.

As noted above, concentration is substantially higher in regimes of medium technological complexity. Under those regimes, the outcome that is most strongly related to the industry wage share is market concentration. The more concentrated the market, the lower the wage share in final demand. As the top-left panel of Figure 2 shows, the relation is rather similar across the different eco-systems, although market concentration is higher and the wage share lower under the 'gestation' eco-system. Public investment improves both, at the same rate. Such a relation is not observed for an environment of high technological complexity, in which market concentration is relatively low.

In a nutshell, when the public sector is only involved during the gestation phase of the technology life-cycle ('gestation' eco-system), *and* private firms are able to reap shares of financial rewards from the innovation process that are disproportionate to their contributions to the process (i.e. higher private RRN), higher innovation diffusion (i.e. final demand) is associated with increases in industry concentration (i.e. higher Herfindahl index) and profit/wage inequality (i.e. lower wage share in final demand). When, instead, the public sector is more actively involved throughout the innovation chain (as in the 'licensing' and 'grants' eco-systems), it is possible to accelerate innovation diffusion *without* increasing inequality.

6 Final remarks

The present report has explored some relationships between innovation performance, market structure, profit/wage gap and public/private inequality, by comparing different types of innovation 'eco-systems', in an emerging industry undergoing a process of technological and market competition. Eco-systems have been defined by the asymmetric public/private role in financing innovation and the associated complexity of the new technology introduced into the economy.

Three *stylised* 'eco-systems' have been proposed. In all three of them the public sector is involved in the process of technological exploration by directly investing in R&D at early stages of the innovation chain (i.e. gestation phase). Differences on its role emerge once the potential market size (i.e. technological opportunities) allows for private firms to enter the market.

Within the first, 'gestation' eco-system, it is *only* up to private firms to further finance the innovation process after the gestation phase of the technology life-cycle. In the second, 'licensing' eco-system, the public sector directly invests in R&D *throughout* the innovation chain, and private firms pay a license fee to access accumulated public knowledge. Finally, in the third, 'grants' eco-system the public sector supports private firms throughout the technology-life cycle by allocating grants to further (co-)finance innovation. All three eco-systems have been analysed for alternative complexity levels of the new technology introduced into the economy.

Moreover, we have argued how each stylised eco-system depicted could be linked to narratives behind actual innovation processes: features of the 'gestation' eco-system may be related to the pharmaceutical industry, those of the 'licensing' eco-system have been inspired by the development of some of Apple's iPhone components, and the 'grants' eco-system could be related to the development of solar PV panels in the US.

The tool used to numerically explore relationships between innovation and inequality within this framework has been an agent-based simulation model introduced in Wirkierman et al. (2018), further augmented and adapted to contemplate different institutional arrangements and public/private redistribution mechanisms, as required by each eco-system. Simulation exercises have focused on better understanding the interplay between innovation diffusion, the distribution of gains between public and private actors, between industry profits and wages, and the implications of this for industrial dynamics.

In our assessment of average trends between scenarios, the 'grants' eco-system emerges as one with high innovation diffusion (i.e. market size given by the percentage of adopters), industry concentration and failure rates similar to the 'licensing' eco-system and an intermediate degree of imbalance between risk taking and profit sharing, when comparing public and private agents. That is, high innovation performance, relatively low profit/wage gap, and an intermediate private/public Reward/Risk imbalance.

Thus, in applied terms, the setting-up of joint (public/private) research labs, financed out of public grants (i.e. associated to the 'grants' eco-system) – and which are active *throughout* the innovation chain – would appear as a desirable intermediate case (in terms of balancing innovation performance and relative inequalities), under an environment of medium technological complexity.

By comparing co-movements of variables across simulation runs, it emerged that when the public sector is only involved during the gestation phase of the technology life-cycle ('gestation' eco-system), *and* private firms are able to reap shares of financial rewards from the innovation process that are disproportionate to their contributions to the process (in terms of risk taken), higher innovation diffusion is associated with increases in industry concentration and profit/wage inequality. When, instead, the public sector is more actively involved throughout the innovation chain (as in the 'licensing' and 'grants' ecosystems), it is possible to accelerate innovation diffusion *without* increasing inequality. Ultimately, precisely because innovation is a collective and cumulative process, Reward/Risk imbalances may not only result in greater inequality but also undermine the innovation process itself.

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