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Abstract

We study the impact of alternative innovation policies on the short- and long-run performance of the economy, as well as on public finances, extending the *Schumpeter meeting Keynes* agent-based model (Dosi et al., 2010). In particular, we consider market-based innovation policies such as R&D subsidies to firms, tax discount on investment, and direct policies akin to the "Entrepreneurial State" (Mazzucato, 2013), involving the creation of public research-oriented firms diffusing technologies along specific trajectories, and funding a Public Research Lab conducting basic research to achieve radical innovations that enlarge the technological opportunities of the economy. Simulation results show that all policies improve productivity and GDP growth, but the best outcomes are achieved by active discretionary State policies, which are also able to crowd-in private investment and have *positive hysteresis* effects on growth dynamics. For the same size of public resources allocated to market-based interventions, "Mission" innovation policies deliver significantly better aggregate performance if the government is patient enough and willing to bear the intrinsic risks related to innovative activities.

Keywords: innovation policy, mission-oriented R&D, entrepreneurial state, agent-based modelling.

JEL codes: O33, O38, O31, O40, C63.

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1 Introduction

In this paper, we extend the *Schumpeter meeting Keynes* agent-based model (Dosi et al., 2010) to assess the impact of different innovation policies on the short- and long-run performance of the economy, as well as on the public budget.

The stagnating aftermaths of the Great Recession and, more recently, of the COVID-19 pandemics, call for public policies able to restore robust economic growth. Such crises also exacerbated the pre-existing productivity slowdown experienced by most developed economies. This implies that government should introduce policies to influence the pace of innovation and technological change, which are the major drivers of long-run economic growth. The Next Generation EU program released by the European Commission goes explicitly in this direction. However, in our view, the contemporary discourse on innovation policies has been far too narrow, quite disjoint from their implications for the economic and social future of our societies. In fact, it is remarkable that, in the past, some of the most important "innovation policies" were not called as such. The Manhattan Project, the Apollo Program, Nixon's "war on cancer" were not discussed, if at all, as "policies" but as major societal objectives, well shielded from the narrow concerns of economists' cost-benefit analyses. On the contrary, nowadays, innovation policies – except for war-related innovations and pandemic emergencies - have to pass through the dire straits of *efficiency* criteria. However, even on these narrower grounds, we shall show, innovation policies are well worth.

Innovation policies (written large, and meant to include science and technology policies) broadly refer to the design of a variety of instruments aimed at generating new knowledge, new products and more efficient production techniques (within an enormous literature, see from Bush et al., 1945 to Freeman and Soete, 1997; Edler and Fagerberg, 2017; Criscuolo et al., 2020). Depending on the type and scope of the policy tools employed, innovation policy might require more or less extensive involvement of the public sector in the economy. A broad distinction is between *indirect* and *direct* innovation policies (Dosi, 1988; Dosi and Nelson, 2010; Mazzucato and Semieniuk, 2017). Indirect policies tend to be "market-friendly" as they provide monetary incentives to firms to improve their innovative performance (e.g. R&D subsidies) or to speed-up their technological renewal (e.g., investment tax discount). In an influential debate at the OECD in the early 80s, they were called "diffusion-oriented" policies (Ergas, 1987). Differently, direct innovation policies imply an active of role of the public sector in shaping the rates and directions of innovative activities, which means - to paraphrase Nelson (1962) - shaping technological landscape and search regimes, taking risks that private businesses are not willing to sustain, and pursuing pathbreaking technological developments. Direct innovation policies respond to Freeman (1987) plea for policies creating systems and institutions able to nurture the generation and diffusion of new knowledge across the economy, the creation of new industries and markets and - ultimately - to fuel economic growth. These policies may certainly be facilitated by an *Entrepreneurial State* (Mazzucato, 2013) that takes the lead and directly invests in the search for novel technological opportunities (possibly directed to specific missions; see also Mazzucato, 2018a and Mazzucato, 2021).

The ability of alternative innovation policies to spur innovation, crowd in private investment and deliver sustained long-run growth is highly debated. Notwithstanding a large body of studies evaluating single policies (see Becker, 2015, for a survey), systematic comparisons of policy designs are scarce in the literature (Grilli et al., 2018), especially from a macroeconomic perspective (Di Comite and Kancs, 2015). A recent review by Bloom et al. (2019) discusses pros and cons of various instruments, suggesting a trade-off between the short run, where tax incentives and subsides are effective in stimulating innovation, and long run outcomes, which would benefit from systemic investments in universities and education. However, Bloom and co-authors overlook (or dismiss) *direct policies*, based on the argument that the effects of these policies are hard to be identified econometrically. In addition, those policies, it is suggested, lack an economic rationale - of course in terms of the conventional economic theory, according to which were it not for market failures and externalities, one better leave the market and the search for innovations to itself.

In this work, we shall indeed show the robust rational of direct policies in complex evolving economies. We extend the *Schumpeter meeting Keynes* (K+S) macroeconomic agent-based model (Dosi et al., 2010) to systematically compare the impact of direct and indirect innovation policies on economic performance, while accounting for their impact on the public budget. [1] In that, the paper also contributes to the literature about modelling of R&D, innovation activities and their impacts on the macroeconomy, integrating the representation of technological change, its sources and consequences within an agent-based perspective (for germane contributions see Russo et al., 2007; Dawid et al., 2008; Lorentz et al., 2016; Caiani et al., 2019; Dosi et al., 2019; Fagiolo et al., 2020 and the survey in Dawid, 2006).

The K+S model is composed of two vertically-related sectors, wherein heterogeneous firms strive to develop new technologies and locally interact by exchanging capital-goods in a market with imperfect information. This is the Schumpeterian engine of the model: new machine tools are discovered and diffuse within the economy both via imitation activities of competing capital-good producers and via investment by consumption-good firms. Firm investment depends on firm demand expectations, as well as on their financial conditions and it constitutes, together with worker consumption and public expenditures, the Keynesian soul of the model. Aggregate demand dynamics in the model affects not only business cycles, but also the pace of technological change (see e.g. Dosi et al., 2016). The K+S model is therefore able to go beyond the traditional separation between “coordination" and “change" in economics (Dosi and Virgillito, 2017).

Indeed, the K+S family of models represents flexible environments which can be used as virtual laboratories for policy experiments to investigate a variety of policy interventions and perform counterfactual analyses. We examine four innovation policy regimes and their possible combinations, namely (i) R&D subsidies to capital-good firms; (ii) tax-discounts on consumption-good firms' investments; (iii) the creation of a public research-oriented capital-good firm; (iv) the institution of a National Research Laboratory which tries to discover radical innovations that enlarge the set of technological opportunities available in the economy. The first two experiments mimic indirect innovation policies, while

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[1] Agent-based models are particularly suited to evaluate different combinations of policies in frameworks characterized by deep uncertainties, technical and structural change. More on that in Fagiolo and Roventini (2017); Dosi and Roventini (2019); Dawid and Delli Gatti (2018). We also suggest to look at Dosi et al. (2020) for a systematic comparison of market-based and industrial policies in fostering catching-up.

the latter pair captures key features of direct or "Entrepreneurial-State" policies. Finally, we consider a benchmark scenario where the public resources are used to support private consumption instead of innovation policies.

Simulation results show remarkable differences across innovation policy regimes. First, all innovation policies spur productivity and GDP growth, but to different degrees, while this is not the case for transfers to households. Second, the impact of direct innovation policies is larger vis-à-vis indirect ones and entails effects of *positive hysteresis* (Dosi et al., 2018; Cerra et al., 2021) putting GDP on higher growth trajectories. However, Entrepreneurial-State policies are risky: their positive impact tend to show up on longer time horizons as compared with indirect interventions, and they can fail to discover new technologies. Nonetheless, extensive Monte Carlo analyses show that, on average, direct innovation policies deliver higher productivity and GDP growth, while being less expensive in terms of net public resources, compared to "indirect" forms of intervention. The impact of Entrepreneurial-State interventions is stronger when they combine the presence a public firm with a National Research Laboratory. Conversely, indirect monetary incentives tend to be associated with some redundancy – that is transfer of resources to firms with little effect on the intensity of search. Finally, all innovation policies we consider crowd in private R&D investment (in line with Moretti et al., 2019 and Pallante et al., 2020), although direct interventions provide, again, the most bang for their buck. Accordingly, our results suggest that the type of tools utilised by a mission-oriented Entrepreneurial State (Mazzucato, 2013, 2018a, 2021) are also more effective at meeting uncontroversial innovation policy goals of productivity and growth gains.

To sum up, our results indicate that innovation policies are highly effective. In particular, when public resources are concentrated on clear missions and Entrepreneurial-State interventions, they appear to deliver large gains in economic performance compared to policies based on monetary incentives. This should be taken into account by policy makers when designing vast policy plans such as the Next Generation EU to jump-start growth in economies hardly hit by the COVID-19 crisis.

The rest of the paper is organized as follows. Section 2 provides a critical overview of the literature on innovation policies. In Section 3, the K+S model is introduced. The empirical validation of the model is performed in Section 4. In Section 5, we present the results of innovation policy experiments. Finally, Section 6 concludes the paper.

2 Innovation policies: a critical review

Economic theory identifies innovation as the most relevant driver of industrial development, specialization and long-run economic growth. This holds true both in neoclassical (Solow, 1957; Romer, 1986; Aghion and Howitt, 1992) and evolutionary theories (Nelson and Winter, 1982; Dosi, 1982; Dosi et al., 1994). However, the underlying views about how knowledge evolves, accumulates, diffuses and - ultimately - affects productivity are profoundly different across these two theoretical paradigms (see Dosi, 1988; Dosi and Nelson, 2010, among others). Such differences also often map into opposing prescriptions with respect to innovation policy.

We define innovation policies, to repeat, as the set of attempts carried out by a government to shape or influence the generation and diffusion of new knowledge and new technologies. All this can be implemented either via monetary instruments, regulations or direct interventions, often but not always with the purpose of increasing productivity and economic growth. Some other times, they can be just be an unintended consequence of policies meant to achieve other purposes – e.g. winning a war (Moretti et al., 2019; Gross and Sampat, 2020). But what motivates innovation policies themselves?

The *market view* closely based on a neoclassical perspective basically justifies policies only in presence of market failures or untraded externalities. Assuming in a first approximation the equivalence between technological knowledge and information, the latter has an intrinsic public-good nature, implying an endemic tendency to underinvest in expensive activities of search by private profit-motivated agents (Arrow, 1951, 1962), which can be mitigated by various forms of transfers and incentives. Another way to partially align incentives to innovate by private actors and social objectives – as a good deal of the current narrative goes, vastly overstretching the implication of Arrow's argument – entails the deepening and strengthening of Intellectual Property Rights (IPR) thus supposedly increasing the equilibrium rates of allocation to R&D investments, etc. There are many reasons why this argument is very weak.

Let us start with the "market failure" approach, appealing as it is for its simplicity, which indeed continues to be influential among policy makers (OECD, 2010; EU, 2020) and economists alike. However, it is theoretically flawed and empirically unfounded. On the theoretical side, the argument is postulated on the difference between ideal "complete markets" and actual ones. But if this is so, the whole world is a huge market failure: there is hardly any market which looks like a complete market in the Arrow-Debreu sense (more in Stiglitz, 1996; Cimoli et al., 2009)! Indeed, there is a fundamental incompatibility between innovation and general equilibrium, basically for two reasons. First, if an innovation is a true innovation, one cannot know about it ex ante, otherwise it would not be an innovation: therefore it is also impossible to attribute probabilities to its occurrence, let alone having "rational expectations" about them and their mapping into expected costs. Thus, markets must be incomplete by definition. Second, the very presence of technological knowledge (Arrow calls it "technical information") implies an extreme form of increasing returns and thus ubiquitous non-convexities, multiple equilibria, or non-existence of equilibrium at all (see Arrow, 1996 and the comments by Arrow in Teece, 2019). Of course, with that disappears all the welfare properties of general equilibrium, taken for granted in "market failure" evaluations. Analytically, "computable general equilibria", often used to plug innovation into aggregate models, in this context, is just an oxymoron. The "market failure argument" is misleading also for other reasons. Indeed, the equivalence between knowledge and information is just a first rough approximation: while information can be easy to access, the same does not necessarily hold for knowledge. Not all knowledge can be codified: much economically useful knowledge is tacit and heterogeneously distributed across actors and contexts (Polanyi, 1944; Nelson and Winter, 1982; Dosi, 1988; Winter, 1998; Metcalfe, 2005; Dosi and Nelson, 2010).

More generally, the empirical evidence supporting any link between incentives and propensity to innovate is at best fuzzy. First, the empirical evidence supporting the effectiveness of monetary subsidies and stronger IPR regimes to stimulate private R&D spending is rather weak (Zúñiga-Vicente et al., 2014; Dimos and Pugh, 2016; Papageorgiadis and Sharma, 2016), despite the fact that these policies typically entail large fiscal costs. Indeed, firms might tend to keep their R&D steady and simply exploit public subsidies and tax-credits to boost their profits (Marino et al., 2016; Mohnen et al., 2017). Second, stronger IPRs might not matter significantly in firm-level decisions and can even decrease the long-run pace of innovation (Dosi et al., 2006; Dosi and Stiglitz, 2014; Cimoli et al., 2014; Stiglitz, 2014). For example Levin et al. (1987), Fagerberg (2017) and Cohen (2010) show that in most industries firms are not much concerned about the lack of strong IPR as the capabilities underpinning their innovative performance cannot be copied easily (Dosi and Nelson, 2010; Edler and Fagerberg, 2017). On the contrary, many firms have close interactions and knowledge exchanges with relevant parties (e.g., customers, suppliers, universities, public research institutions, etc.) which nurture the transfer of tacit knowledge during the innovation process.

Furthermore, the market failure approach is even less useful when radical technological change is needed (see Mazzucato, 2016). Private businesses tend to invest in new technologies only after the high risks and uncertainty have been absorbed by research and development activities directly funded by the public sector. In this case, mission-oriented policies are needed to create new technologies, new sectors and new markets (Foray et al., 2012). Such innovation policies consider the public sector as an *Entrepreneurial State* mostly engaged in industry creation and market shaping rather than market fixing, actively setting new innovation directions towards significant social goals (missions). The idea of market shaping and mission-orientation has began to gained acceptance in recent years in Europe where it seems to be adopted by the European Commission - in relation to grand societal challenges such as the green transition (Mazzucato, 2018b, 2019). This finally reflects disappointment in the ability of market fixing approaches to address these challenges and recognition that the appetite for risk, long term thinking and capacity for coordination in the private sector is inadequate for producing a decisive shift in the direction of innovation (Mazzucato and Semieniuk, 2017, 2018). Public policies must therefore support all phases of the innovation process, taking risks (and possible losses) that the private sector will not absorb, waiting patiently for the rewards of innovation and coordinating activities across public and private stakeholders (Mazzucato, 2013). Perhaps less widely acknowledged is the economic case for a mission-oriented Entrepreneurial State. The economic impacts from such policies are often hard to quantify empirically, being associated with dynamic spillovers, even when the social ones are quite obvious. A priori, we would expect Entrepreneurial State policies to have high potential for generating growth due to the fact they target new markets, technologies and directions of discovery. This means they have also the potential to create opportunities for advancement in productivity, consumer demand, international competitiveness and so forth which would not be created by the private sector alone (Mazzucato, 2013, 2018a).

The historical record provides compelling cases in support of this. Governments invested directly in the technologies that enabled the emergence of mass production and IT revolutions and undertook the bold policies required to deploy them throughout the economy (Block and Keller, 2015; Ruttan, 2006). Many of the examples of this relate to the pervasive impact of military and space innovation (the

Manhattan project, the Apollo program and ARPANET - the progenitor of the internet - are among the most famous; see Gross and Sampat, 2020, 2021) but, more recently, successful results have been highlighted across many other technological landscapes, including the biotechnology industry (Lazonick and Tulum, 2011), nanotechnologies (Motoyama et al., 2011), and the emerging clean-tech sector (Mazzucato, 2015; Steffen et al., 2020).

Beyond the selection of the missions to pursue, which reflects broader societal and political objectives, the Entrepreneurial State approach to innovation policy can be summarized across three defining features (Mazzucato, 2016). First, public organizations should experiment, conduct research, learn and take risks. Second, policy design should create symbiotic private–public partnerships, overtaking the idea of de-risking the private investment and fostering a collaborative environment, characterized by joint R&D projects to create new products and services (e.g., new vaccines; Chataway et al., 2007), and crowding-in of private investment (see for example Engel et al., 2016; Moretti et al., 2019; Pallante et al., 2020). Finally, it should provide a system of rewards for the public sector to ensure the long run sustainability of the high risk-taking investments described above, as well as for public accountability purpose.

One of the implications of the "market failure approach" is that it calls for the state to intervene as little as possible in the economy, in ways that minimize the risk of "government failures", whatever that means in complex evolving economies. A corollary is also the drive to outsource the innovation process from public organizations to private firms.

To the contrary, a mission-oriented Entrepreneurial State aims at shaping the direction of technological change, employing a mix of indirect instruments (schemes of incentives) and, much more important, direct interventions (e.g. through public agencies, formal public-private collaborations, use of public banks to finance bold R&D projects), and coordinating the governance of the whole innovation chain.[2] Under this perspective, the State should not limit itself to provide funding for basic knowledge and help protecting innovation through implementation of IPRs, as the market failure theory would suggest, but also identify and rectify such systemic problems coordinating all levels of public administration and private stakeholders (Metcalfe, 1994, 1995; Edquist, 2011).

3 The K+S model

We investigate which type of innovation policies is more effective in stimulating innovation, productivity and output growth in the Schumpeter meeting Keynes model extended to account for radical innovations and the variable cost of public debt (Dosi et al., 2010, 2013).[3] Our stylized representation

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[2] In this respect, various similarities are shared with the so-called "system-oriented" innovation policies (Edler and Fagerberg, 2017), which builds on the literature on National (Freeman, 1987; Lundvall, 1988, 2010) and Sectoral (Malerba, 2002) Innovation Systems and looks at the systemic nature of the innovation process as emerging from the interaction of a number of factors, including knowledge, skills, financial resources, demand etc. When the system does not sufficiently provide for those factors or fails at coordinating them, a "system failure" may hamper innovation activity.

[3] See also Dosi et al. (2017) for a survey about the Schumpeter meeting Keynes family of models. Indeed, the K+S model has been extended to account for multiple banks and fiscal-monetary policy trade-offs (Dosi et al., 2015), decentralized interactions in the labour market (Dosi et al., 2017, 2021) and the coupled dynamics of climate and economic growth (Lamperti et al., 2018a,

of an economy is composed of a machine-producing sector composed of F_1 firms, a consumption-good sector composed of F_2 firms, an ecology of consumers/workers, and a public sector. Capital-good firms invest in R&D and produce heterogeneous machines. Consumption-good firms combine machine tools bought by capital-good firms and labour in order to produce a final product for consumers. The public sector levies taxes on firms' profits, pay unemployment benefits, and implement the selected innovation policies.

3.1 Innovation and technological progress

The Schumpeterian engine of the K+S model stems from the innovation and imitation search of *capital-good* firms, which produce machine-tools using labour only. The technology of the machines of vintage τ is captured by the couple of coefficients $(A_{i,\tau}, B_{i,\tau})$, where the former represents the productivity of machines employed in the consumption-good industry, while the latter indicates the productivity of the production technique needed to manufacture the machine. Given the monetary wage, $w(t)$, paid to workers, the unitary cost of production of capital-good firms is given by:

$$c_i^{cap}(t) = \frac{w(t)}{B_{i,\tau}}. \tag{1}$$

Similarly, the "quality" of the machines captured by $(A_{i,\tau})$ defines the unitary production cost of consumption-good firms (indexed by j):

$$c_j^{con}(t) = \frac{w(t)}{A_{i,\tau}}. \tag{2}$$

Capital good firms adaptively strive to increase market shares and profits trying to improve their technology via innovation and imitation. They are both costly processes: firms invest in R&D a fraction of their past sales in the attempt to implement incrementally new technologies, discover radically new innovations and imitate more advanced competitors. More specifically,

$$RD_i(t) = \upsilon S_i(t-1), \qquad \upsilon \in \{0,1\} \tag{3}$$

indicates firm i's spending in R&D, which is split into in-house (incremental) innovation (IN_i) and imitation (IM_i) activities:

$$IN_i(t) = \xi RD_i(t), \qquad IM_i(t) = (1-\xi) RD_i(t), \qquad \xi \in [0,1]. \tag{4}$$

As in Dosi et al. (2010), innovation and imitation are depicted as two-steps processes. The first step captures firms' search for new technologies through a draw from a Bernoulli distribution, wherein the real amount invested in R&D (i.e. the number of hired researchers) positively affects the likelihood of success. More precisely, the parameters controlling the likelihood of success in the Bernoulli trial for

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2019, 2020, 2021).

the innovation and imitation process, $\theta_{IN}(t)$ and $\theta_{IM}(t)$ respectively, correspond to:

$$\begin{aligned}\theta_{IN}(t) &= 1 - e^{-o_{IN} IN_i(t)}, \quad o_{IN} > 0, \qquad (5)\\ \theta_{IM}(t) &= 1 - e^{-o_{IM} IM_i(t)}, \quad o_{IM} > 0; \qquad (6)\end{aligned}$$

where the parameters $0 < -o_{IN}, o_{IM} \leqslant 1$ capture the search capabilities of firms.

The second step differs for innovation and imitation activities. Let us consider innovation first. Successfully innovating firms will access a new technology, whose technical coefficients are equal to:

$$\begin{aligned}A_{i,\tau+1} &= A_{i,\tau}(1 + \chi_{A,i}) \qquad (7)\\ B_{i,\tau+1} &= B_{i,\tau}(1 + \chi_{B,i}) \qquad (8)\end{aligned}$$

where $\chi_{A,i}$ and $\chi_{B,i}$ are independent draws from a $Beta(\alpha, \beta)$ distribution over the support $[\xi_1, \xi_2]$, with $\xi_1 < 0$ and $\xi_2 > 0$. The support captures the technological opportunities available for the firms. Note that as $\chi(t)$ is allowed to be negative, the newly discovered technology may be inferior to the current one. This reflects the intrinsic trial and error process associated to any search for new technologies.

Successful imitators have the opportunity to copy the technology (embodied in the two technical coefficients A and B) of one of their competitors. The imitation probability negatively depends on the technological distance between each pair of firms. More precisely, the technological space is modelled as a 2-dimensional Euclidean space (A, B), where ℓ^2 is chosen as the metric determining distance between couples of points:

$$TD_{i,j} = \sqrt{(A_i - A_j)^2 + (B_i - B_j)^2}, \qquad (9)$$

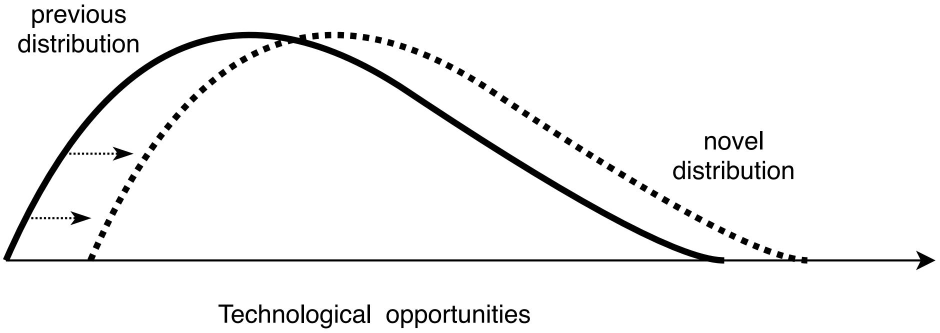
where the vintage of the technology employed by firms i and j is dropped to ease notation. For each imitator, competitors are ranked according to their (normalized) technological distance $NTD_{i,j} = TD_{i,j} / \sum_j TD_{i,j}$ and a draw from a uniform distribution on the unitary interval determines the firm whose technology will be imitated.

When a novel technology is developed or imitated, firms decide whether to adopt it or not by comparing its overall costs through the following routine:

$$\min[p_i^h(t) + bc^{con,h}] \;\; h \in \{in, im, \tau\}, \qquad (10)$$

where b is a payback parameter (more on that in Section 3.2), p is the price of the machine and c is the unitary production cost a firm would incur in employing the imitated (im), newly developed (in) or incumbent (τ) technology. Once the machine to put in production is selected, capital-firms fix the price as a constant mark-up on their unit cost of production. The capital-good market is characterized by imperfect competition: capital-good firms advertise their product to their historical customers, as well as to a subset of potential new ones.

Figure 1: Shift of technological opportunities implied by radical innovations



Beyond in-house incremental innovations and imitation, we allow for the discovery of *radical innovations*, which are intended here as innovations that change the technological landscape and increase the technological opportunities available in the economy. Examples of such radical innovations include electricity, energy storage and the Internet. Following the lines of Mazzucato (2013), these innovations are rarely the outcome of a single research project within private businesses, but more likely depend on a broader, systemic effort encompassing both public (from basic to applied) and private research, often carried out through private-public collaborations and characterized by sequences of trials and errors (see also Mowery, 2010; Block and Keller, 2015 and the discussion in section 2). To capture these features, we model radical innovations as shifts of the support $[\xi_1, \xi_2]$ of the distribution of technological opportunities available to the firm (see also Figure 1):

$$\xi_1^{RI} = \xi_1 + \chi^{RI}, \qquad \xi_2^{RI} = \xi_2 + \chi^{RI}. \tag{11}$$

The probability of discovering a radical innovation depends positively on the cumulative R&D expenditures performed by the capital-good firm (CRD_i) and by public research agencies (CRD_{public}). Private cumulative R&D, $CRD_i(t) = \sum_{s<t} RD_i(s)$, proxies the stock of knowledge generated by the firm over time in their search efforts. The probability (P_i^{RI}) that a capital-good firm i discovers a radical innovation enlarging the technological opportunities is then equal to:

$$P_i^{RI}(t) = f\left(x \,|\, x = \frac{CRD_i(t) + CRD_{\text{public}}(t)}{GDP(t)}\right) = \frac{1}{1 + e^{\eta_1 (x - \eta_2)}}, \tag{12}$$

with $\eta_1 > 0$ and $\eta_2 > 0$ controlling the shape of the logistic function. Indeed, there is robust evidence supporting a non-linear positive association between a sufficiently large stock of cumulated knowledge and the discovery of breakthrough innovations (Phene et al., 2006; Dunlap-Hinkler et al., 2010; Kaplan and Vakili, 2015). Enlarged technological opportunities diffuse though the capital-good sector via the imitation of competing firms. However, radical innovations are more difficult to copy as they increase the technological distance between the firm mastering the new state-of-the-art technology and its competitors.

3.2 Investment and technological diffusion

Firms in the *consumption-good industry* produce a homogeneous good using their stock of machines and labor under constant returns to scale. They invest to expand their capital stock and/or to replace their obsolete machines with new ones. Note that such investments contribute to the technological diffusion of state-of-the-art technologies in the economy.

Let us first consider expansionary investment. Firms face a demand created by the expenditures of workers, and plan their production according to (adaptive) expectations over such a demand, desired inventories, and their stock of inventories.[4] Whenever the capital stock is not sufficient to produce the desired amount, firms invest (EI_j) in order to expand their production capacity:

$$EI_j(t) = K_j^d(t) - K_j(t), \tag{13}$$

where K_j^d and K denote the desired and actual capital stock respectively.

Further, firms invest to replace current machines with more technologically advanced ones according to a payback period routine. In a nutshell, they compare the benefits entailed by new vintages embodying state-of-the-art technology vis-á-vis the cost of new machines, taking into account the horizon in which they want to recover their investment. In particular, given the set of all vintages of machines owned by firm j at time t, the machine of vintage τ is replaced with a new one according to:

$$\frac{p^{new}}{c_j^{con}(t) - c^{new}} = \frac{p^{new}}{\left[\frac{w(t)}{A_{i,\tau}}\right] - c_j^{new}} \leq b \tag{14}$$

where p^{new} and c^{new} are the price and unitary cost of production associated to the new machine and b is a parameter capturing firms' "patience" in obtaining net returns on their investments.[5] The vintages of machines that satisfies Eq. 14 constitute the replacement investment of the firm, $SI_j(t)$. Aggregate investment just sums over the investments of all consumption good firms:

$$I_j(t) = EI_j(t) + SI_j(t). \tag{15}$$

As the capital-good market is characterized by imperfect information, consumption-good firms choose their capital-good supplier comparing price and productivity of the currently manufactured machine-tools. The model thus entails local interaction among heterogeneous suppliers and customers.[6]

Consumption-good firms sets the price of their final good applying a variable mark-up on their

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[4] In the benchmark setup, expectations are myopic. The results are robust for different expectation formation mechanisms. More on that in Dosi et al. (2020).

[5] Our assumptions are in line with a large body of empirical literature showing that replacement investment is typically not proportional to the capital stock, but a crucial strategic decision of firms (see e.g. Feldstein and Foot, 1971; Eisner, 1972; Goolsbee, 1998).

[6] More on that in Dosi et al. (2010). Note also that machine production is a time-consuming process: consumption-good firms receive the ordered machines at the end of the period. This is in line with a large body of literature: see, e.g., Rotemberg (2008) for details on pricing, imperfect information and behavioural attitudes of consumers and Boca et al. (2008) for the presence of gestation lag effects in firms' investments.

unit cost of production. In line with the evolutionary literature and a variety of "customer market" models (Phelps and Winter, 1970), the mark-up changes over time according to the evolution of firm's market shares: firms increase prices if their market share is rising and decrease it when the market share falls. Consumers have imperfect information regarding the final product (see Rotemberg, 2008 for a survey on consumers' imperfect price knowledge) which prevents them from instantaneously switching to the most competitive producers. For this reason, market competition is captured via a replicator dynamics: the market share of firms more competitive than the industry average increases, while that of less competitive ones shrinks over time. Firms' competitiveness depends on their price and on their capacity to satisfy demand in the past.[7]

At the end of each period, consumption-good and capital-good firms compute their profits and update their stock of liquid assets. Firms with zero market shares or negative net assets die and a new breed of firms enters the market. Overall, the number of firms is fixed, hence any dead firm is replaced by a new one. In line with the empirical literature on firm entry (Bartelsman et al., 2005), we assume that entrants are on average smaller than incumbents, with the stock of capital of new consumption-good firms and the stock of liquid assets of entrants in both sectors being a fraction of the average stocks of the incumbents. Concerning the technology of entrants, new consumption-good firms select amongst the newest vintages of machines, while the technology of new capital-good firms is on average worse than incumbents' ones.

3.3 The public sector and the macroeconomic framework

Workers-consumers have a marginal propensity equal to one in the model. Accordingly, aggregate consumption (C) is computed by summing up over the income of both employed and unemployed workers:

$$C(t) = w(t)L^D(t) + w^U[L^D(t) - L^S(t)], \tag{16}$$

where w represent wages, w^U the unemployment subsidy and L^D and L^S labour demand and labour supply respectively. Wages are linked to the dynamics of productivity, prices and unemployment rate by the following wage equation:

$$w(t) = w(t-1)\left[1 + \psi_1 \frac{\Delta \bar{A}B(t)}{\bar{A}B(t-1)} + \psi_2 \frac{\Delta cpi(t)}{cpi(t-1)} + \psi_3 \frac{\Delta U(t)}{U(t-1)}\right], \tag{17}$$

where $\bar{A}B$ indicates the average productivity in the economy, cpi is the consumer price index and U stands for unemployment rate. The labor market does not necessarily clear and both involuntary unemployment and labor rationing can occur.

The unemployment subsidies - a fraction of the current market wage - are paid by the public sector (G indicates such spending), which also levies taxes on firm profits. Taxes and subsidies are the fiscal leverages that contribute to the aggregate demand management regimes. Further, the government can

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[7] Unfilled demand is due to the difference between expected and actual demand. Firms set their production according to the expected demand. If a firm is not able to satisfy the actual demand, its competitiveness is accordingly reduced. On the contrary, if expected demand is higher than actual one, inventories accumulate.

run innovation policy incurring in additional spending as indicated by IP (more on that in section 5). The deficit is then equal to:

$$Def(t) = G(t) - Taxes(t) + CD(t) + IP(t), \tag{18}$$

where CD indicates the cost of public debt (i.e. interests on previous debt) and satisfies $CD(t) = r_{pd}(t)PD(t-1)$, with PD denoting the stock of public debt and $r_{pd}(t)$ the interest rate. Differently from Dosi et al. (2010), the interest rate on government bonds changes over time according to the ratio between the public debt and GDP:

$$r_{pd}(t+1) = r_{pd}(t) + \varrho \frac{PD(t)}{GDP(t)}, \tag{19}$$

with $\varrho > 0$. The above assumption allows one to capture the long-run cost of innovation policies and the possible emergence of vicious debt cycles triggered by excessive public expenditures.[8]

Finally, the model satisfies the standard national account identities: the sum of value added of capital- and consumption goods firms equals aggregate production that, in turn coincides with the sum of aggregate consumption, investment and change in inventories:

$$\sum_i Q_i(t) + \sum_j Q_j(t) \equiv Y(t) \equiv C(t) + I(t) + \Delta N(t), \tag{20}$$

where Q_i and Q_j represent the production of capital and consumption good firms respectively and ΔN stands for the variation of inventories.

4 Simulation set-up and empirical validation

The foregoing model does not allow for analytical, closed-form solutions. This is a distinctive feature of many ABMs that stems from the non-linearities present in agent decision rules and their interaction patterns, and it implies running computer simulations to analyze the properties of the stochastic processes governing the coevolution of micro and macro variables (more on that in Windrum et al., 2007; Fagiolo and Roventini, 2017; Fagiolo et al., 2019). In what follows, we therefore perform extensive Monte-Carlo analyses to wash away cross-simulation variability. More precisely, all results are presented either as single simulation runs, to show the behaviour of our artificial economy along a hypothetical scenario, or as averages across two-hundreds independent simulations to identify robust emerging properties and to perform statistical testing across scenarios and policy experiments.

Before running policy experiments, the model has undergone an indirect calibration exercise. Then we "empirically validate" the model, i.e. we study its capability to account for a large ensemble of macro and micro stylized facts (see Fagiolo et al., 2019, and the Appendix for additional details). This is done

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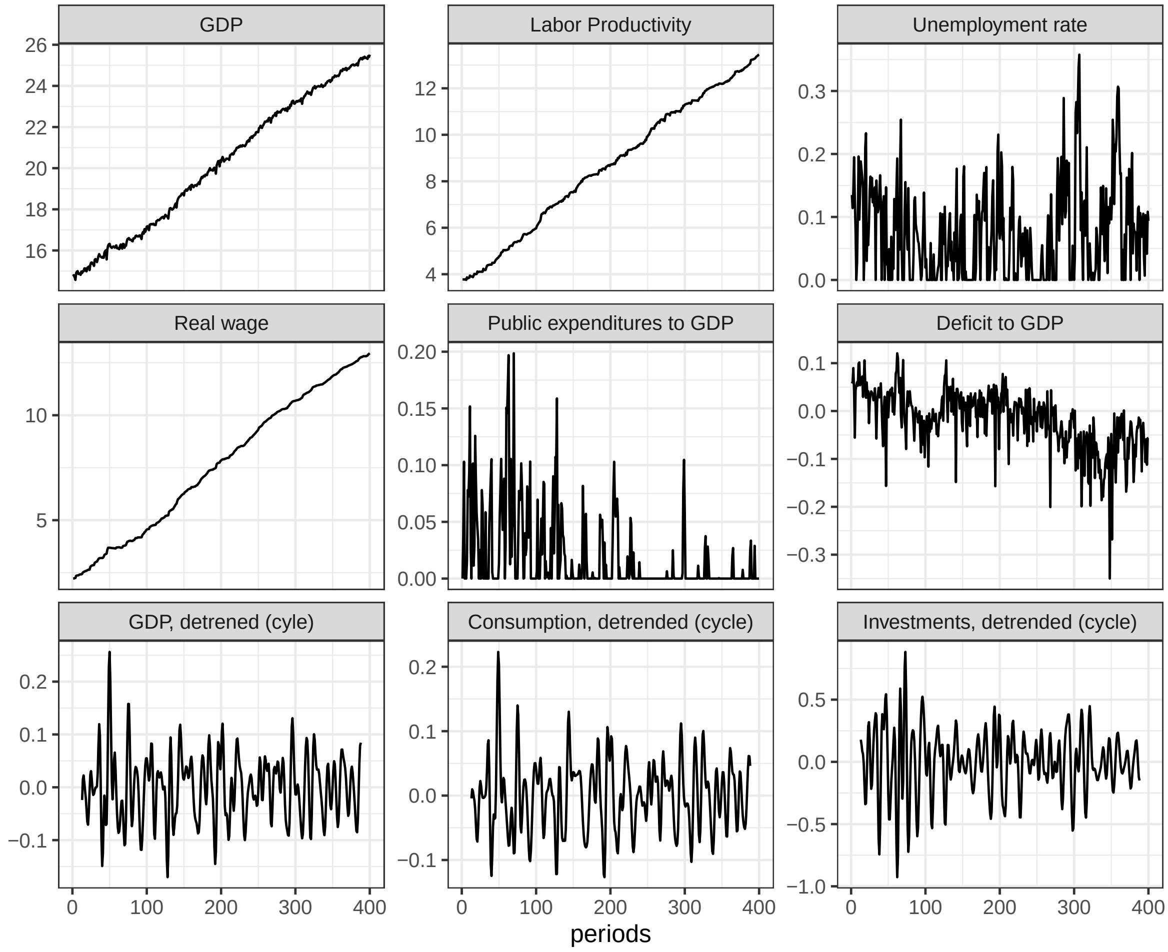
[8] For more experiments on the short- and long-run impact of fiscal policies on public debt as well as economic dynamics, see Dosi et al. (2015).

Figure 2: Model behaviour under the “no innovation policy” baseline. Selected indicators are reported for a single model run. GDP, Labour productivity, Real wage are in logs. Negative public deficit indicates a surplus.



in the “no innovation policy” scenario, whose parameter configuration is reported in the Appendix.[9]

Figure 2 shows the dynamics of the model in the “no innovation policy” baseline relying on a single model run, while Table 1 reports a series of summary statistics over the Monte Carlo ensemble. The model robustly generates endogenous self-sustained growth patterns characterized by the presence of persistent fluctuations and rare crises. The positive trend in productivity and aggregate output is driven by the innovation activity of capital-good firms and the processes of technological diffusion occurring horizontally via the imitation activity of competitors, as well as vertically through the investment choices of consumption-good firms.

Simulation results also show the presence of fierce Schumpeterian competition taking place at the microeconomic level. For instance, on average, slightly more than half of capital-good firms successfully introduce an innovation or copy the technology of a competitor in every simulation step, while just

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[9] See also Lamperti (2018b,a), Guerini and Moneta (2017) and Lamperti et al. (2018).

Table 1: Summary statistics for selected indicators in the "no innovation policy" baseline; 200 runs are used. HHI stands for Hirschman-Herfindahl Index; Cap-Good indicates the Capital Good sector and Cons-Good the Consumption good sector; Lik. stands for Likelihood; incr. and rad. for incremental and radical respectively. Crises are defined as events where either GDP drops by more than 3% in a single period or four consecutive periods of negative growth are observed.

Variable	**Mean**	**St. Dev**	**Variable**	**Mean**	**St. Dev**
GDP growth	0.0268	0.0012	Unemployment	0.0610	0.0376
GDP volatility	0.0819	0.0005	Productivity growth	0.2581	0.0012
Deficit on GDP	0.0434	0.0553	HHI Cap-Good sector	0.6691	0.0601
Lik. of crises	0.0462	0.0399	HHI Cons-Good sector	0.0032	0.0001
Lik. of (incr.) innovation	0.571	0.0424	Lik. of imitation	0.6012	0.0502
Lik. of (incr.) inno. & imit.	0.218	0.0370	Lik. of (rad.) innov.	$1.25\ 10^{-05}$	0.0000

one-fifth perform both activities. The likelihood of radical innovations is remarkably low, and only a private firm is able to obtain one in a single run.

Government deficit averages around reasonable levels (4-6% of GDP) for a developed economy, while displaying large spikes during crises, characterized by surges in unemployment. Beyond such rare crises, whose likelihood is relatively low (around 5%), public finances often register a surplus, guaranteeing the long run sustainability of debt.

The bottom panels in Figure 2 show the cyclical components of the GDP, consumption and investment time-series generated by our model. They show the presence of vibrant fluctuations in all series, punctuated by deep downturns. Such fluctuations are genuinely endogenous, as no aggregate exogenous shock is present in the model. In addition, consumption and investments are, respectively, more and less volatile than output, in tune with empirical evidence (Stock and Watson, 1999; Napoletano et al., 2006.

The K+S model is also able to account for a wide set of microeconomic empirical regularities concerning e.g. firm size and growth-rate distributions, productivity dynamics, investment patterns. This reflects the strong explanatory capabilities of agent-based models as discussed in Haldane and Turrell (2019) and Dosi and Roventini (2019). Details about the empirically regularities replicated by the K+S model are spelled out in the Appendix (see Table 7) and in Dosi et al. (2017).

Overall, our "no innovation policy" baseline reflects an economy where decentralized interactions give rise to stable properties at the macroeconomic level (all standard deviations in Table 1 are relatively low compared to the averages), with sustained growth and healthy public finances. Against such background we test a series of policy regimes aimed at further stimulating innovation, productivity and long-run growth, while maintaining public deficit and debt under control.

5 Innovation policy experiments

As emphasized in Section 2, innovation policy encompasses a variety of instruments, ranging from monetary incentives such as R&D subsidies and tax credits (indirect interventions) to direct spending in public research activities (for example, in the US, funding basic research through the National Sciences Foundation as well as public organizations like DARPA of the US Department of Defense). In this Section we rely on controlled simulation experiments to investigate the macroeconomic effects of different policy instruments: Section 5.1 first describes the different policy interventions, while simulation results are spelled out in Section 5.2. A sensitivity analysis of the main results can be found in the Appendix (Table 9).

5.1 A "menu" of innovation policies

We consider five different types of innovations policies and we also experiment with ensembles of different interventions. Experiments I and II consider indirect policy interventions typical of the *market failure* approach, whereas Experiments IV and V explore direct Government interventions and are akin to the *Entrepreneurial State* framework. As an additional benchmark, we consider a scenario (Experiment III) where public expenditures sustain only private consumption and hence cannot have a direct influence on productivity growth.[10]

Experiment I: R&D subsidies. The Government provides a R&D subsidy to firms in order to increase their research efforts. Larger R&D investments may increase the chances of discovering novel machines, more efficient production techniques or, finally, they may speed up horizontal technological diffusion via imitation of competitors. We assume that public subsidies $q_{\text{RD}} > 0$ are proportional to firm's past spending in research and innovation (RD_i):

$$RD_i(t) = \upsilon S_i(t-1) + q_{\text{RD}} RD_i(t-1). \tag{21}$$

Experiment II: investment tax discount. Under this intervention, consumption-good firms receive a government-financed discount on their investments in novel capital goods, whose size - relative to the price of the new machine - amounts to d_{TD}. This policy is supposed to speed up technological diffusion vertically, as consumption-good firms pay a lower price whenever they replace current machines with new ones embedding state-of-the-art technologies. Under this policy, the pay-back period routine (cf. Eq. 14) becomes:

$$\frac{p^{new}(1-d_{TD})}{c_j^{con} - c^{new}} \leq b. \tag{22}$$

Experiment III: public expenditures directed to private consumption. This experiment mimics a scenario where public transfers boost household consumption expenditures. Of course, in this framework, they

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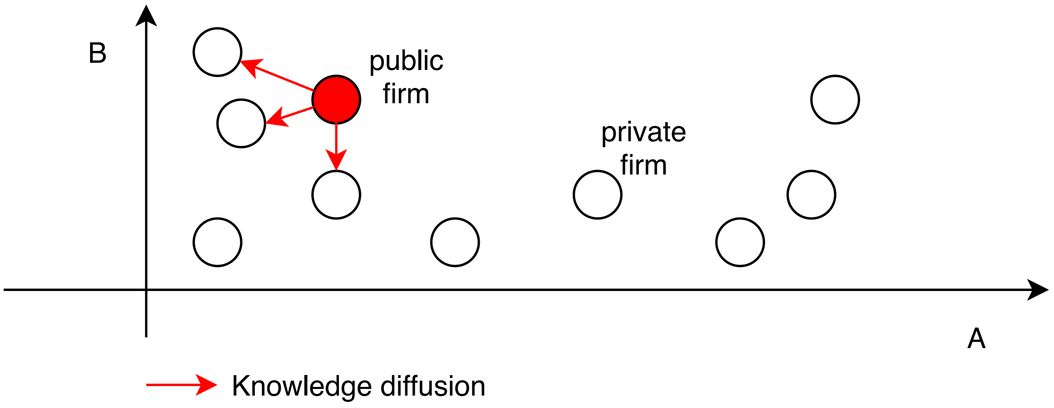
[10] In the model consumption positively affects demand expectations and thus expansionary investment. It may thus have, via this channel, a positive effect on R&D in the capital good sector, which depends on past sales. Nevertheless, its impact is expected to be lower compared to R&D subsidies and direct government innovation policies.

Figure 3: Experiment IV: knowledge diffusion by the public firm



do not directly affect the innovation and investment decisions of firms, but they might increase productivity growth via more sustained levels of aggregate demand.

Experiment IV: a public capital-good firm. In an Entrepreneurial State framework, new public entities are created to shape the innovation landscape by engaging and coordinating research in given fields and diffusing the relevant knowledge to facilitate technological progress (see sections 1 and 2). In this experiment, the government creates and fund a public firm in the capital-good sector. Similarly to privately owned firms, the new public firm satisfies the demand of machines coming from consumption-good firms and performs innovation and imitation activities. However, four key differences apply: i) the public firm allocates all its profits (Π_{pf}) to R&D; ii) it is bailed out by the government in case of failure (negative net liquid assets); iii) it can receive additional funds from the government (IP) to perform extra research activities; and iv) it fosters the diffusion of its technology to its competitors which can freely imitate it if their cumulated knowledge is sufficiently large. In particular, the R&D expenditure of the public firm (pf) amounts to:

$$RD_{\mathrm{pf}}(t) = \upsilon S_{pf}(t-1) + \Pi_{\mathrm{pf}}(t-1) + IP(t). \tag{23}$$

Any capital-good firms i can freely imitate the public firm if its (normalized) technological distance - which stems from the history and direction of its innovations - from the public firm ($NTD_{pf,j}$, cf. Eq. 9) is smaller than a fixed threshold $\phi \in (0,1)$. Figure 3 shows a stylized representation of such a "local" process of knowledge diffusion. Obviously, private firms will decide whether to adopt the technology of the public firm only if it is convenient on the basis of the routine expressed by Equation (10).

Experiment V: a national research laboratory. The last experiment captures another essential feature of an Entrepreneurial State, i.e. the creation and funding of public institutions that discover radical innovations enlarging technological opportunities in the economy (as for national research laboratories and the Internet, see section 2), while bearing the risks and the costs of such ventures. In particular,

Table 2: Results from Experiment I (R&D subsidies). Rows reports the average relative performance of each experiment with respect to the “no innovation policy” baseline (Baseline) over 200 Monte Carlo runs; for example 1.2 indicates that the experiment has produced an average value of the relevant statistic that is 20% higher than in the baseline. Symbol * indicates a statistical significant difference between the experiment and the baseline at 5% as resulting from a t-test on the means. GDP vol. stands for GDP volatility as proxied by the standard deviation of the growth process; Unempl. stands for unemployment and empl. for employment; Deficit and Fiscal cost are expressed as relative to GDP.

	GDP growth	**GDP vol.**	**Unempl.**	**Periods full empl.**	**Deficit**	**Fiscal cost**
Baseline	2.68%	0.08	6.10%	16%	4.34%	0.00
Size of the subsidy						
5%	1.04	1.01	0.98	1.04	1.25	0.9% *
10%	1.08 *	1.02	0.98	1.08	1.39 *	2.2% *
15%	**1.10** *	**0.97**	**0.96**	**1.17** *	**1.14** *	**2.6%** *
30%	1.18 *	0.99	0.95	1.37 *	0.94	6.4% *

we introduce a national research lab (NRL) that (i) performs basic research but does not produce; (ii) takes stock of all the knowledge developed in the economy, (iii) tries to enlarge the set of technological opportunities available for capital-good firms through the discovery of radical innovations (see Section 3.1). At each time step, the NRL receives public funding form the government to perform its research activities. Further, as it is a purely research-oriented organization, it is able to exploit the entire body of knowledge available in the economy to perform its research. Hence, the discovery of a radical innovation by the NRL is assumed to depend on its cumulative search efforts (CRD_{public}), as well as on those performed by capital-good firms (CRD_i):[11]

$$P^{RI}_{NRL}(t) = f\left(x \,|\, x = \frac{\sum_i CRD_i(t) + CRD_{\text{public}}(t)}{GDP(t)}\right) = \frac{1}{1 + e^{\eta_1(x-\eta_2)}}. \tag{24}$$

Differently from private firms (see section 3.1), a NRL that discovers a radical innovation, also provides free access to the new technological opportunities it involves, de facto moving the distribution of innovative possibilities for the whole economy.[12]

5.2 Simulation results

To ensure the comparability of results across the different policy experiments, we keep constant the fiscal cost of the innovation policies in the various regimes. In particular, we first perform Experiment I (R&D subsidy) by setting the size of the subsidy ($q_{RD} \in \{5\%, 10\%, 15\%, 30\%\}$). Then, we inspect the

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[11] To the contrary, the probability that private firms discover a radical innovation depends on own cumulative R&D and the R&D expenditures by the NRL, if any. See Equation 12.

[12] In the current set-up, we cannot study mission-oriented innovation policies directed to specific missions, as the model does not allow for multiple industries. Hence, we cannot study how such policies trigger the direction of technical change through the emergence of new sectors and markets. We leave such developments to future research (see also our discussion in Section 6).

results of the model (see Table 2) and select a reference scenario whose fiscal cost — expressed in terms of average expenditure for the innovation policy relative to GDP — is imposed to all other experiments. In particular we use $q_{RD} = 15\%$ as our reference scenario, where the average cost of the innovation policy amounts to 2.6% of GDP. When running all other experiments, the size of the policy intervention is then equal to $IP(t) = 0.026 \cdot GDP(t)$.

Figures 4 and 5 show the patterns of GDP (and public deficit) for a single run of the five innovation policy experiments. First, all innovation policies have a positive effect on the long-run output trend of the economy (although to different extent). This is not the case for transfers supporting private consumption (Exp. III), which do not have significant effects compared to the baseline scenario. Furthermore, a stark contrast emerges between indirect (Exps. I and II) and direct (Exps. IV and V) innovation policies: while R&D subsidies and tax incentives produce a permanent upward shift in the GDP level compared to the baseline (with subsidies being much more effective than tax-credits, see also Figures 6 and 7), Entrepreneurial State interventions, either in the form of research-oriented public capital good firms or as a national research laboratory, produce robust GDP growth accelerations (see panels A and C of Figure 5).

Direct intervention policies are more effective than indirect ones also as far as the public finances are concerned. Indirect policies generate public deficit-to-GDP ratios that tend to be constant yet higher than in the baseline scenario (see panel B of Figure 7 and Table 3). Entrepreneurial State interventions generate instead deficits-to-GDP ratios that are decreasing over time and that, in the case of experiment V, are lower than in the baseline (see again Table 3).[13] Decreasing deficits-to-GDP ratios are result of the growth accelerations induced by direct innovation policies as the fiscal cost is constant across policy scenarios.

The superior performance of direct innovation policies vis-à-vis indirect ones is confirmed by the summary statistics reported in Table 3. The battery of Monte Carlo statistics shows in particular that Experiment V is the best innovation policy to implement as it solves the growth-deficit trade-off (with respect to the baseline) that characterizes instead all other policy regimes and it guarantees a superior trajectory for the economy characterized by higher average growth, lower unemployment output, and the lowest impact on public finances (the higher volatility is due to the jump in technological opportunities). Experiment IV ranks second as it improves the performance of the economy. However, its lower (positive) impact on growth is not enough to improve the average deficit to GDP ratio with respect to the “no innovation policy” baseline. Indirect innovation policies (Exps. I and II) are more effective to stimulate productivity and GDP growth in the short-run (Figure 6), but they are overtaken by Entrepreneurial-State interventions in the long-run, and they worsen public finances across the whole simulation span. More precisely, tax discount do not significantly improve neither output growth nor the employment rate with respect to the baseline, while R&D subsidies does both. As expected, public transfers to consumption ranks last with a negative impact on GDP growth and public deficit (but lower average unemployment rate).

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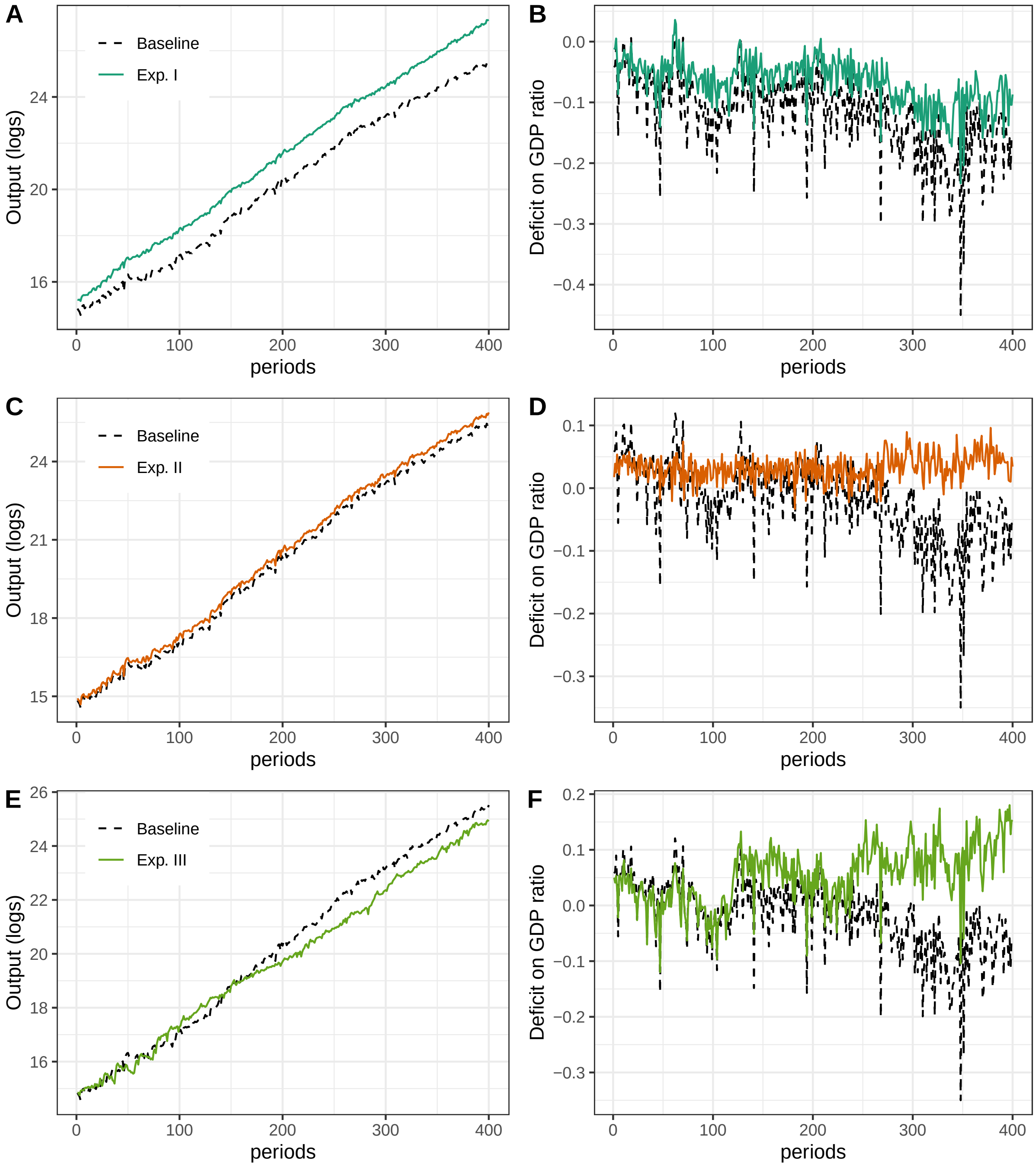
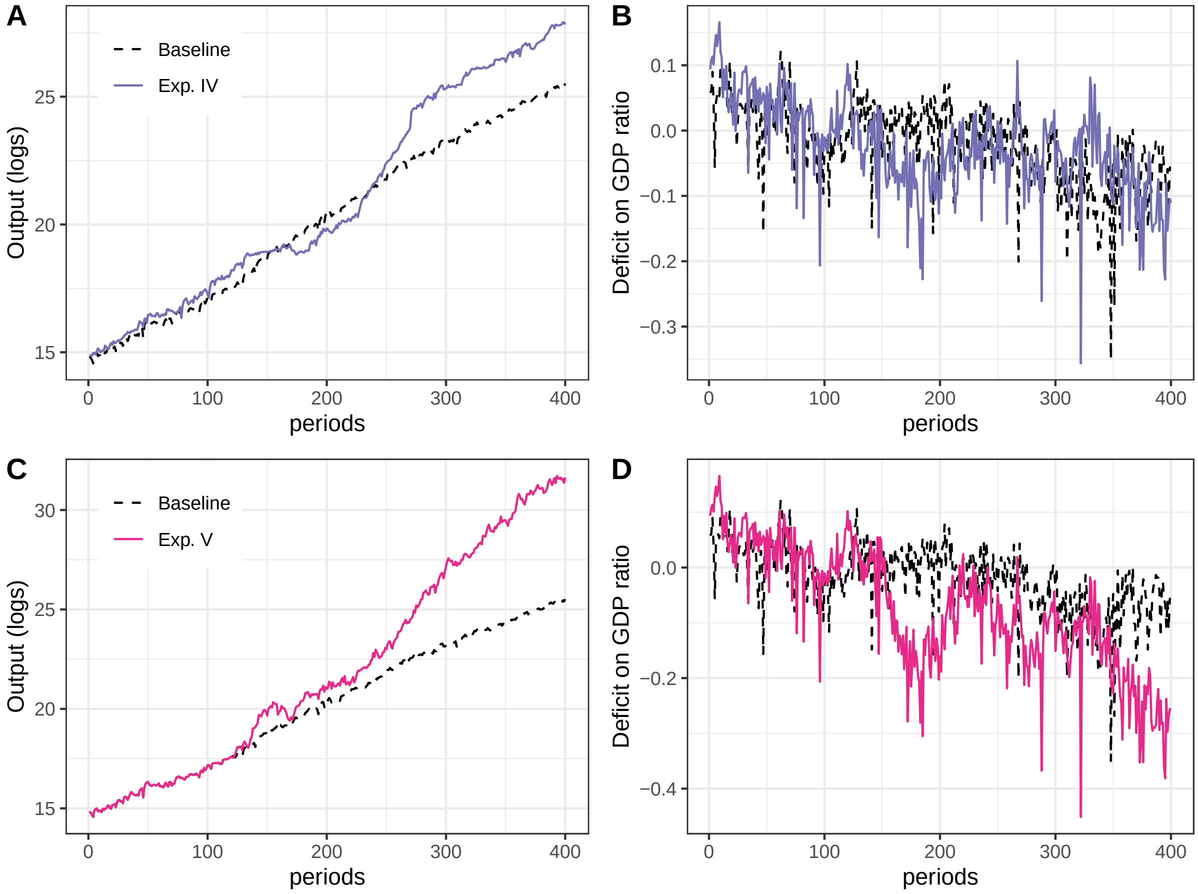
[13] The highest deficit is recorded when public transfers finance private consumption (Exp. III). However, in all policy scenarios the ratio between public debt and GDP does not increase over time.

Figure 4: Dynamics of GDP and public deficit across experiments for indirect innovation policies. Each row of panels corresponds to an experiment: panels A and B to Experiment I (R&D subsidies), panels C and D to experiment II (Investment tax discount), panels E and F to experiment III (Transfers to consumption). Each plot shows a single model run under the experiment and the "no innovation policy" baseline.



We also consider different pairs of innovation policies by equally splitting the public resources across the two interventions, thus guaranteeing comparability with previous (stand-alone) experiments.

Figure 5: Dynamics of GDP and public deficit across experiments for direct innovation policies. Each row of panels corresponds to an experiment: panels A and B to Experiment IV (Public firm) and panels C and D to experiment V (National Research Lab). Each plot shows a single model run under the experiment and the "no innovation policy" baseline.



Simulation results reveals interesting synergies and redundancies across policies (see Table 3). First, the joint implementation of R&D subsidies with Entrepreneurial-State policies (IV+I and V+I) delivers higher output growth and employment levels while shrinking deficits with respect to Experiment I alone. However, such a combination is outperformed by both stand-alone "public firm" and "NRL" interventions (Exps. IV and V). Splitting resources across research subsidies and tax discounts (Exp. I + II) worsen the dynamics of GDP and public finances relative to the Experiments I and II alone, showing the redundancy of incentives to private firms in fostering innovation and growth. Finally, the best policy results are obtained when the synergies between Entrepreneurial-State policies (Exp. V + IV) are fully exploited. Indeed such a policy combination improves the performance of the economy and reduces the deficit-to-GDP ratio vis-á-vis the two interventions in isolation.

Accelerations in either GDP or productivity growth, which underlie the superior performance of direct innovation policies, are the result of *positive hysteresis,* i.e. a permanent increase of the growth

Figure 6: Dynamics of GDP (panel A) and public deficit (panel B) across experiments. Averages over 200 Monte Carlo runs. Exp. I: R&D subsidies; Exp. II: Investment tax discount; Exp. III: Transfers to consumption; Exp. IV: Public firm; Exp. V: National Research Lab.

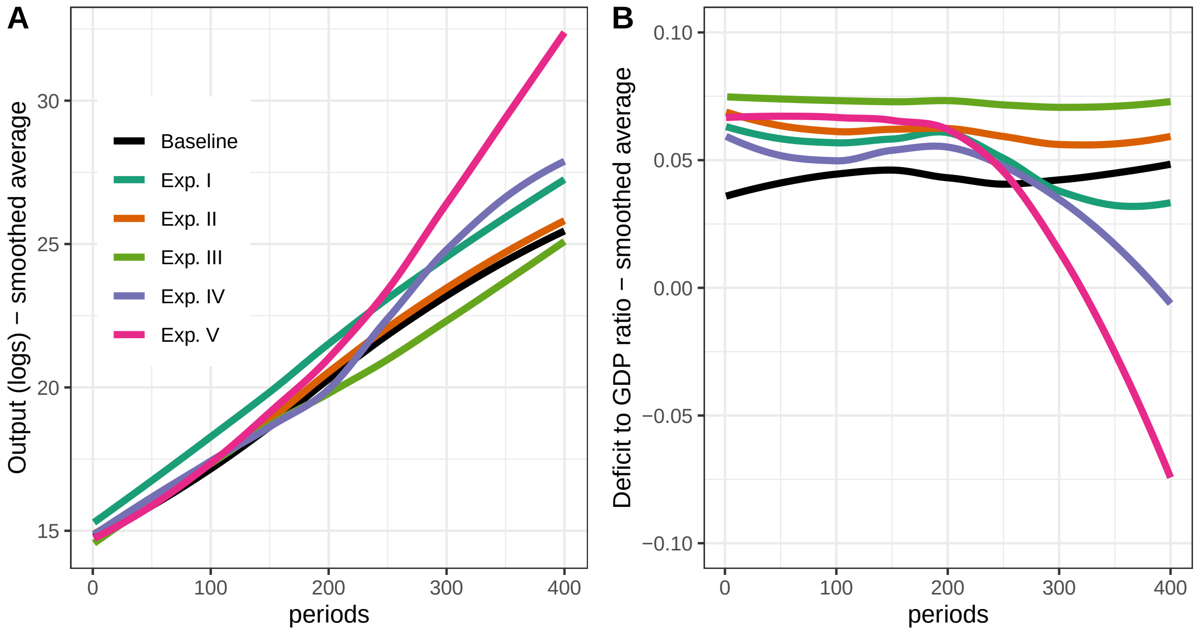


Figure 7: Distribution of GDP growth (panel A) and public deficit (panel B) values across experiments. Pooling of averages over 200 Monte Carlo runs, each observation corresponds to the Monte Carlo average in a given simulation step. Exp. I: R&D subsidies; Exp. II: Investment tax discount; Exp. III: Transfers to consumption; Exp. IV: Public firm; Exp. V: National Research Lab.

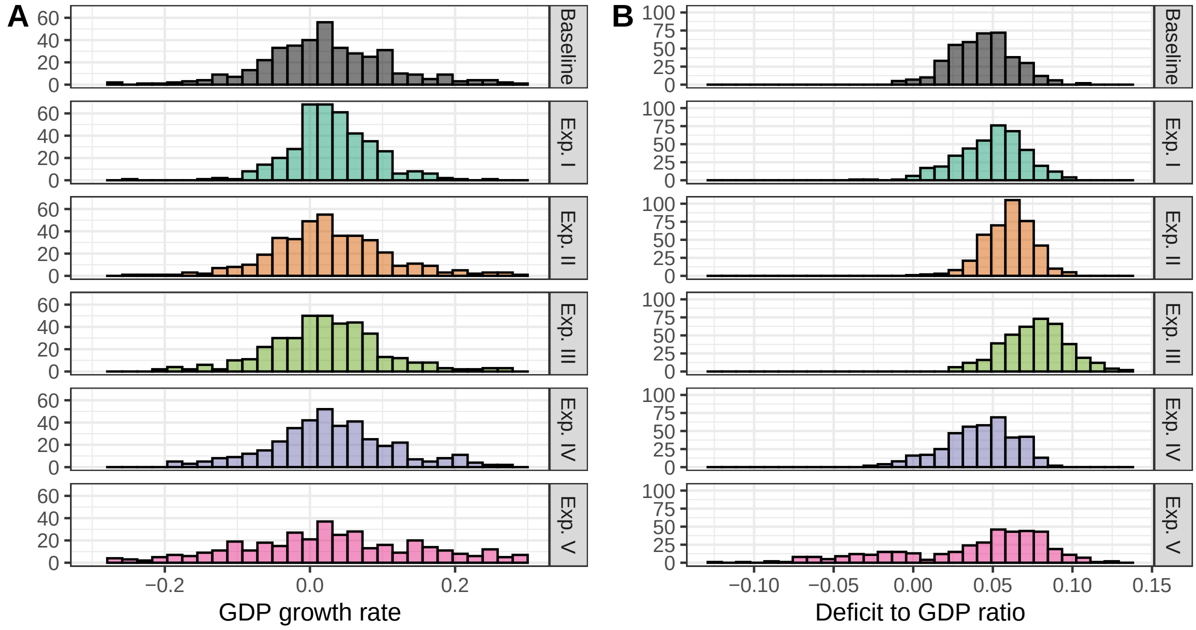


Table 3: Comparison of different innovation policy experiments and their combinations. Rows report the average relative performance of each experiment with respect to the "no innovation policy" baseline over 200 Monte Carlo runs. Symbol * indicates a statistical significant difference between the experiment and the baseline at 5% as resulting from a t-test on the means. GDP vol. stands for GDP volatility proxied by the standard deviation of the growth process; unempl. stands for unemployment and empl. for employment; deficit is expressed as relative to GDP.

Policy	**GDP growth**	**GDP vol.**	**Unempl.**	**Periods full empl.**	**Deficit**
Baseline	2.68%	0.08	6.10%	16%	4.34%
I - R&D subsidies	1.10*	0.97	0.96	1.17*	1.14*
II - Investment tax discount	1.08	1.22*	0.97	1.38*	1.34*
III - Transfers to consumption	0.96*	0.98	0.92*	1.08*	1.45*
IV - Public firm	1.27*	1.53*	0.88*	1.28*	1.19*
V - National Research Lab	1.55*	2.01*	0.88*	1.52*	0.78*
I + II	1.01	0.96	1.13*	1.22*	1.35*
IV + I	1.16*	1.12*	0.94*	1.32*	1.27*
IV + II	1.12*	1.40*	0.96	1.49*	1.34*
V + I	1.37*	1.99*	0.74*	1.36*	0.90*
V + II	1.22*	1.35*	0.87*	1.39*	0.95
IV + V	1.67*	2.60*	0.77*	1.61*	0.77*

possibilities of the economy.[14] For instance, in Exp. IV the public firm induces a rapid and temporary process of knowledge accumulation and diffusion that has positive permanent effects on the level of output. In Exp. V we observe instead *super hysteresis*, i.e. a permanent surge of GDP growth rate. This is explained by the fact that a NRL may introduce radical innovations, which shifts to the right the entire distribution of technological, and thus growth, opportunities. Thus, while almost all hysteresis literature focuses on the long-lasting impact of recessionary shocks on employment and GDP (see e.g., Dosi et al., 2018; Cerra et al., 2021), our results show that Entrepreneurial State innovation policies can positively affect the growing possibility of the economy.

Table 4 allows one to better understand the microeconomic drivers of hysteresis in our simulation experiments. During the initial stages of the simulation, i.e. when the innovation policy has still to exert its effects, the public firm is rarely imitated by its private competitors. However, as time goes by, the higher R&D propensity of the public firm maps into more innovations which move its technology towards the frontier and thus increase the imitation rates of its private counterparts. In turns, the sustained imitation process spurs the diffusion of state-of-the-art technologies in the economy and triggers the temporary GDP growth accelerations shown in panel C of Figure 5. However, this process eventually stops (see panel C of Figure 5 and panel B of Figure 6) and the aggregate growth rate of the economy falls back to previous levels, for two reasons. First, the public firm extracts productivity gains from a constant technological opportunity landscape. This sets an upper bound on the productivity gains it can diffuse to the rest of the economy. Second, most firms are able to catch up the technology

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[14] In macroeconomics, hysteresis is defined as a situation where a shocks permanently affect the path of the economy.

Table 4: Experiment IV: imitation of the public firm. Values represent the average number of times the public firm is imitated by a private firm in each simulation span and over 200 Monte Carlo runs (capital good sector is composed of 50 firms)

	Per-period imitations of the public firm			
	Mean	Max	Min	St. Dev.
Simulation span				
[1-100]	0.7	3	0	1.8
[101-200]	2.2	7	0	2.5
[201-300]	4.6	8	0	3.1
[301-400]	1.8	4	0	2.2

of the public firm over time. The latter is therefore less and less imitated over time (cf. the lower imitation rates in the last part of the simulation in Table 4), which introduces a further slow-down on the overall growth process.

The ability of the public firm to trigger a diffusion process stimulating productivity and output growth correlates robustly to its degree of *technological embeddedness* (Figure 8), defined as the average technological distance between the public firm and its private competitors (see Equation (9) in Section 3.1). Simulation runs wherein the private firms are able to quickly catch-up the public one display - ceteris paribus - higher productivity growth (Figure 8). These results deliver two policy implications: (i) Entrepreneurial-State-like policies may need time to display their positive results, especially at the macroeconomic level; (ii) the position of public firms in the technological space can play a significant role in boosting the growth rate of the economy.

A NRL-based direct innovation policy thus delivers a superior performance - on average- compared to indirect policies. At the same time, it may also imply some risks, which are associated to the ability of this policy to effectively trigger technological breakthroughs that enlarge the set of technological opportunities. Figure 9 shows the dynamics of GDP and of the deficit-to-GDP ratio in five selected runs, which capture two qualitatively opposite patterns associated with that policy. In the first one, output growth exhibits a positive structural break and *super hysteresis* emerges. This virtuous dynamics is triggered by the discovery of radical innovations by the NRL and its subsequent diffusion in the economy. On the contrary, in the second pattern shown in the figure, the R&D activity by the National Research Lab is not able to deliver a major technological breakthrough. In this case, the innovation policy does not spur GDP growth, but it raises the public deficit and the ratio between public debt and output (cf. Figure 9), resembling those displayed in Experiment III (i.e. unproductive spending; see panel F in Figure 5). Such simulation results clearly reveal the perils of Entrepreneurial State policies wherein for every winning investment there are many possible failures (Mazzucato, 2016).[15] Nonetheless, the likelihood of these failed trajectories remains limited. The distributions of the average deficit and debt-to-GDP ratios emerging from the Monte Carlo exercise suggest that in Exp. V, the public R&D

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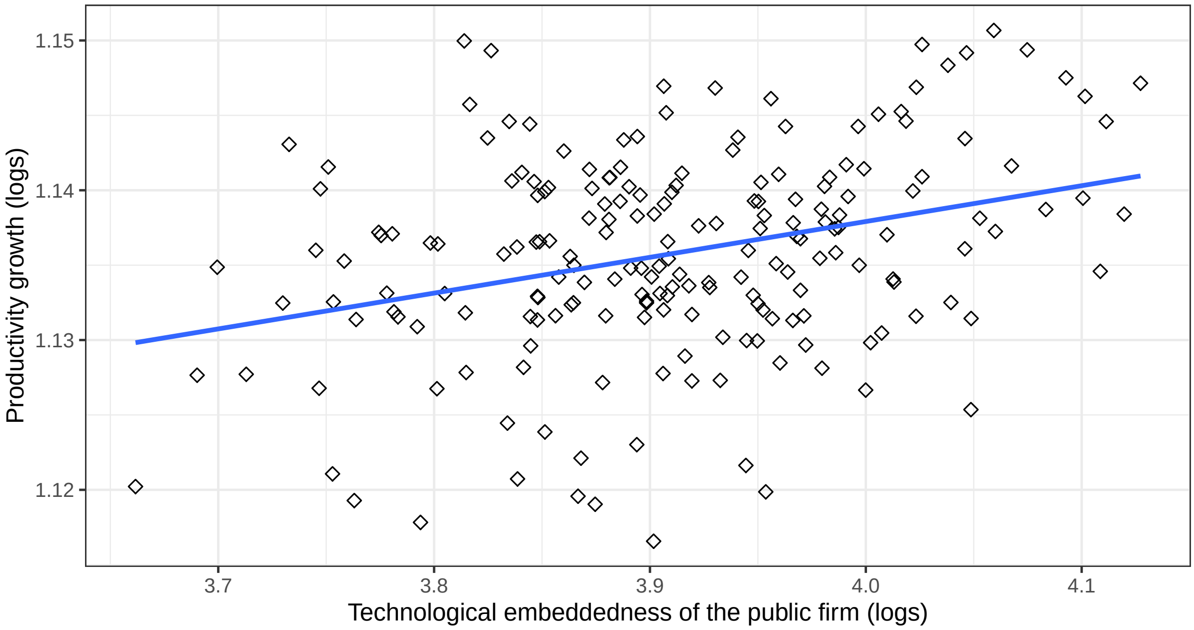
[15] For example, the US Department of Energy provided large-scale guaranteed loans to two green-tech companies: Solyndra ($500 million) and Tesla Motors ($465 million). While the latter is regarded as a success story, the former went bankrupt with a loss for the public agency.

Figure 8: Technological embeddedness of the public firm and aggregate productivity growth in the economy under Experiment IV (Public firm). Each point represents the average over a Monte Carlo run; 200 runs are used.



investment, which, to repeat, is comparable to that of other ones, lead most of the time to the discovery of a radical innovation that keep public finance under control or even in surplus (see also Figure 10).

Finally, we investigate whether public innovation policies crowd out or crowd in private R&D expenditures. In particular, in line with Moretti et al. (2019), we study the possible *additionality* of innovation policies relative to firms' R&D investment, by performing OLS regressions on the artificial data generated by different policy experiments:[16]

$$\log RD_{i,s,t} = \beta_1 \log IP_{s,t-1} + \beta_2 \log GDP_{s,t-1} + \lambda_i + \mu_s + \nu_t + \varepsilon_{i,s,t} \tag{25}$$

where RD refers to private R&D, IP indicates the monetary size of the innovation policy and λ_i, μ_s and ν_t are individual-level, model-run level, and period-level fixed effects. Econometric results show that innovation policies produce significant *crowding-in* of private R&D expenditures across all experiments (Tables 5 and 6). However, stark differences emerge in the impact of different policies. The estimated elasticity of private R&D to public research-related spending ranges from 0.07 (Exp. II) to 1.3 (Exp. IV + V), with the elasticity of R&D subsidies (Exp. I) being at an intermediate level between such boundaries yet delivering a positive significant effect (which is consistent with recent evidences, see Santoleri et al.,

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[16] Our artificial economy offers a convenient setting to estimate Equation (25) across different experiments: multiple model runs are independent by construction, while offering across-run variability ensured by the stochastic nature of the model; the size of the innovation policy is comparable both across experiments and time and individual-level fixed effects absorb firm-specific shocks that differentiate capital-good businesses in our economy.

Figure 9: Dynamics of GDP (panel A) and public deficit (panel B) in Experiment V (National Research Lab), multiple runs in different shades of color.

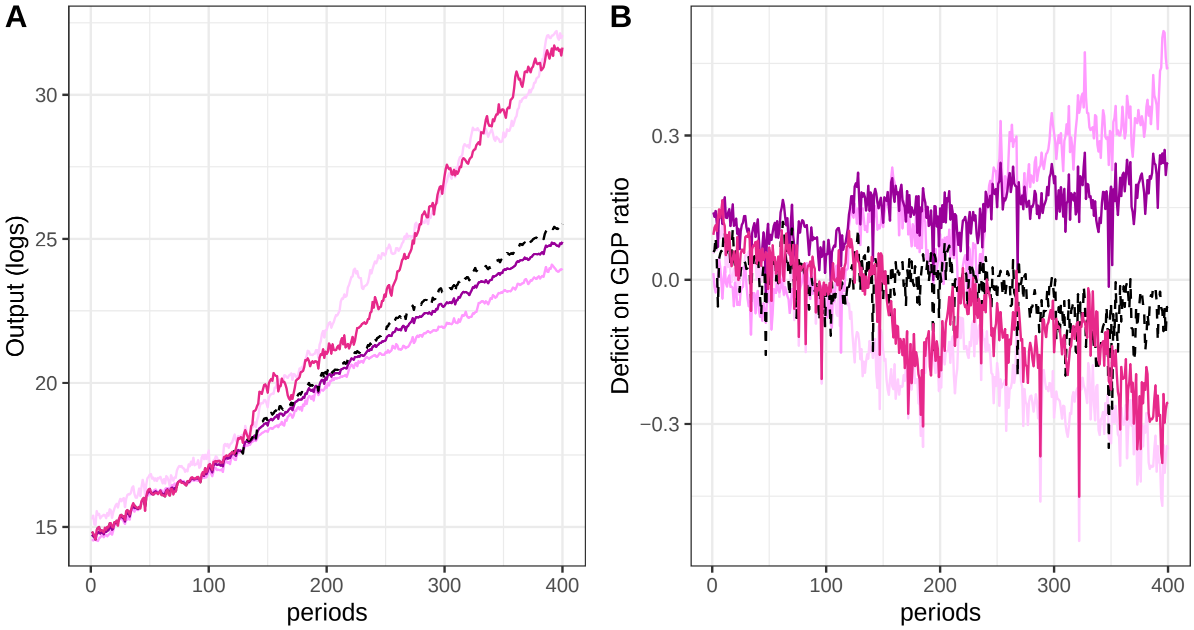

Figure 10: Status of public finances under Experiment V (National Research Lab); panel A reports the distribution of simulation-average deficits and panel B the distribution of simulation-average debt; 200 runs are used. The blue line indicates the mean while the dashed red line crosses the x-axis at zero.

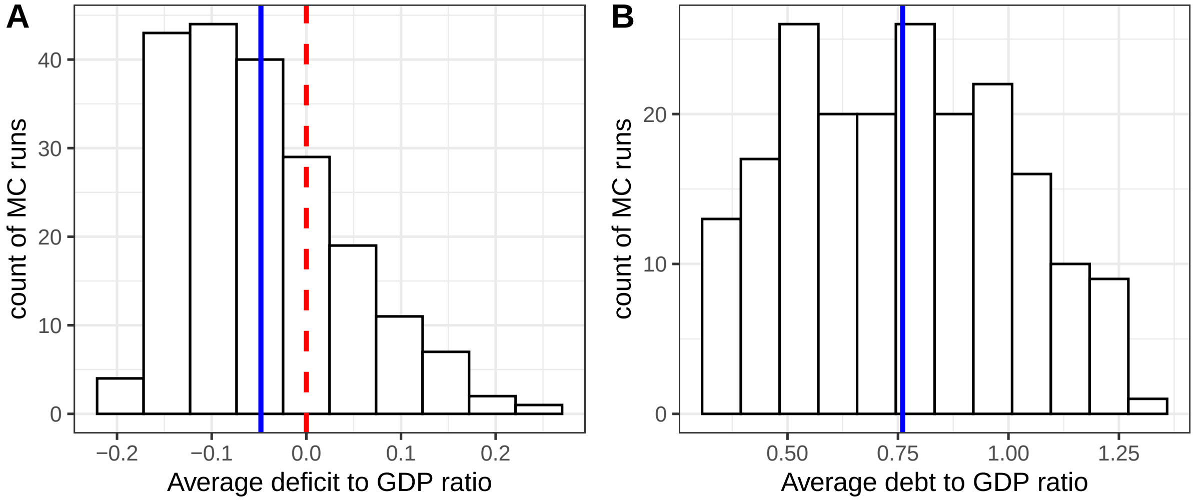

Table 5: Crowding-in of private investments in R&D. Each column reports the estimates of Equation (25) using data relative to different experiments; 200 Monte Carlo runs are employed. Exp. I: R&D subsidies; Exp. II: Investment tax discount; Exp. III: Transfers to consumption; Exp. IV: Public firm; Exp. V: National Research Lab.

	Dependent variable: log firm R&D(t)					
	(baseline)	(Exp. I)	(Exp. II)	(Exp. III)	(Exp. IV)	(Exp. V)
log public R&D(t-1)	0.000	0.643^{***}	0.066^{***}	-0.031^{*}	0.594^{***}	0.511^{**}
	(-)	(0.005)	(0.009)	(0.018)	(0.011)	(0.241)
log GDP(t-1)	0.784^{***}	0.533^{***}	0.660^{***}	0.659^{***}	0.572^{***}	0.589^{***}
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Individual-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Period-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Run-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1960000	1960000	1960000	1960000	1960000	1960000
Adjusted R^2	0.4600	0.4732	0.4287	0.4101	0.5654	0.4932
F Statistic	$243,119,189^{***}$	$288,637,079^{***}$	$65,888,745^{***}$	$57,034,106^{***}$	$57,034,106^{***}$	$57,034,106^{***}$
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 6: Crowding-in of private investments in R&D. Each column reports the estimates of Equation (25) using data relative to different experiments; 200 Monte Carlo runs are employed. Exp. I: R&D subsidies; Exp. II: Investment tax discount; Exp. III: Transfers to consumption; Exp. IV: Public firm; Exp. V: National Research Lab.

	Dependent variable: log firm R&D(t)					
	(baseline)	(Exp. V+I)	(Exp. V+II)	(Exp. IV+I)	(Exp. IV+II)	(Exp. IV+V)
log public R&D(t-1)	0.00	0.631^{***}	0.460^{***}	0.931^{***}	0.531^{***}	1.330^{***}
	(-)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
log GDP(t-1)	0.784^{***}	0.560^{***}	0.580^{***}	0.560^{***}	0.560^{***}	0.540^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Individual-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Period-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Run-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1960000	1960000	1960000	1960000	1960000	1960000
Adjusted R^2	0.4802	0.4758	0.5804	0.5698	0.5554	0.5960
F Statistic	$243,119,189^{***}$	$297,909,025^{***}$	$255,425,660^{***}$	$408,800,073^{***}$	$264,841,402^{***}$	$565,446,088^{***}$
Note:						*p<0.1; **p<0.05; ***p<0.01

2020, and references therein). Remarkably, these results are qualitatively and quantitatively comparable to those of Moretti et al. (2019) on OECD countries (who report an elasticity of private to public R&D of about 0.6%) and of Pallante et al. (2020) on the US (who find that private R&D increases by more than 0.1% for every additional percentage point of spending in public mission-oriented research). Table 6 further confirm the synergies between direct policy interventions (with the elasticity of private R&D corresponding to 1.3 when Exp. V is combined with exp. IV, against 0.6 for Exp. I and 0.5 for Exp. II), which maximize the crowding in of private investments.

6 Conclusions

If and how innovation policies should be designed is one of the major challenges facing policy makers and societies at large. This work contributes to the ongoing debate extending the *Schumpeter meeting Keynes* agent-based model (Dosi et al., 2010) to assess the impact of different public innovation interventions on the short- and long-run performance of the economy, as well as on the public budget. More precisely, we have considered indirect innovation policies supporting the R&D activity and capital-good investment of private firms and direct intervention encompassing a public firm developing new technologies and freely diffusing them into the economy, as well as a National Research Laboratory (NRL) engaged in frontier research to discover radical innovations. The last two policies are akin to the interventions implemented by an *Entrepreneurial State* (Mazzucato, 2013).

Our results show that the most effective innovation policies involve the creation of public research bodies, which we label National Research Labs. Such a policy can lead to radical innovations that enlarge the set of technological opportunities available to private firms, and trigger the emergence of *positive hysteresis* dynamics. The outcome is a higher growth potential of the economy and a lower unemployment rate while the public deficit is kept under control. Positive synergies can be activated combining the previous policy with the creation of a public firm developing new technologies and easing technological diffusion of state-of-the-art capital goods. Indirect innovation policies also increase economic growth while keeping the public budget under control. However, their impact is lower than the one of direct policies. Entrepreneurial-State policies comes with the risk of deteriorating public finances in those cases where the publicly-discovered technologies do not diffuse enough or large-scale and high-risk research projects seeking radical innovations fail. However, for the same amount of public resources allocated to market-based interventions, Entrepreneurial-State innovation policies deliver significantly better aggregate performances if the government is willing to patiently bear the intrinsic risks related to innovation. Finally, in line with the empirical evidence (Moretti et al., 2019; Pallante et al., 2020), we find that innovation policies *crowd-in* private R&D investment. Such a result is stronger for direct innovation policies. Overall, our findings support the idea that public policies aimed at stimulating basic research improve the economic performance (see e.g., Akcigit et al., 2020), but in contrast with Bloom et al. (2019), we show a clear economic rationale for mission-oriented research programs which strengthens both recent empirical evidence (Pallante et al., 2020) and the historical analysis of large government-led research programs (Gross and Sampat, 2020, 2021).

This work can be extended along several directions. First, one could study the impact of innovation policies targeting workers' skills, which would constrain the discovery and diffusion of new technologies. This could be done starting from the labour-augmented K+S model (see Dosi et al., 2020, 2021, and references therein). Second, one could consider the possible interactions between innovation policies and the financial sector, and the possible introduction of a development bank extending the framework in Dosi et al. (2015). Third, one could study mission-oriented innovation policies triggering clear missions, such as the fight to climate change and the orderly decarbonization of the economy. Such interventions could be studied in an extended version of the Dystopian Keynes meet Schumpeter model (Lamperti et al., 2018b, 2019, 2020, 2021), which builds on the shoulders of the baseline model analysed here.

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Appendix

Indirect calibration and stylized facts replication

The model has undergone an indirect calibration exercise (Windrum et al., 2007). In particular, the parameter space has been explored (through random sampling and in absence of innovation policy) in search of the three properties listed below, a best candidate vector of parameters has been chosen and - finally - a series of validation tests based on stylized facts replications have been performed. The three properties we looked for are: (i) long-run growth and business cycles punctuated by infrequent yet possibly deep crises, (ii) a sustainable pattern of deficits reflecting a balanced fiscal policy and (iii) a vivid process of firm competition sustained by innovation and imitation with very rare yet possible radical innovations. Such an approach guarantees a good degree of empirical validity to our simulation experiments and finds in line with the prevailing practices in the agent-based economic literature (Fagiolo et al., 2019).[17] That said, we stress that our exercises should be taken much more as thought experiments aimed at unveiling mechanisms and comparing policies rather than quantitative predictions. Table 7 shows the stylized facts that the model replicates. We point the reader to Dosi et al. (2017) for a more detailed overview of these facts and to the Laboratory for Simulation Development website for the code of the K+S model (without innovation policies), which can be used to generate the data and inspect the stylized facts.

Table 7: Main empirical stylized facts replicated by the DSK model.

Stylized facts	**Empirical studies (among others)**
Macroeconomic stylized facts	
SF1 Endogenous self-sustained growth with persistent fluctuations	Burns and Mitchell (1946); Kuznets and Murphy (1966) Zarnowitz (1985); Stock and Watson (1999)
SF2 Fat-tailed GDP growth-rate distribution	Fagiolo et al. (2008); Castaldi and Dosi (2009) Lamperti and Mattei (2018)
SF3 Recession duration exponentially distributed	Ausloos et al. (2004); Wright (2005)
SF4 Relative volatility of GDP, consumption and investments	Stock and Watson (1999); Napoletano et al. (2006)
SF5 Cross-correlations of macro variables	Stock and Watson (1999); Napoletano et al. (2006)
SF6 Pro-cyclical aggregate R&D investment	Wälde and Woitek (2004)
Microeconomic stylized facts	
SF7 Firm (log) size distribution is right-skewed	Dosi (2007)
SF8 Fat-tailed firm growth-rate distribution	Bottazzi and Secchi (2003, 2006)
SF9 Productivity heterogeneity across firms	Bartelsman and Doms (2000); Dosi (2007)
SF10 Persistent productivity differential across firms	Bartelsman and Doms (2000); Dosi (2007)
SF11 Lumpy investment rates at firm-level	Doms and Dunne (1998)
SF12 Firm bankruptcies are counter-cyclical	Jaimovich and Floetotto (2008)

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[17] See Reissl et al. (2021) for a recent application of an indirect calibration approach to a quantitative oriented macro-economic input-output agent-based model.

Parameters' table

Table 8: Model's main parameters and initial conditions.

Description	**Symbol**	**Value**
Monte Carlo replications	MC	200
Time steps in economic system	T	400
Number of firms in capital-good industry	F_1	50
Number of firms in consumption-good industry	F_2	200
Capital-good firms' mark-up	μ_1	0.02
Consumption-good firm initial mark-up	$\bar{\mu}_0$	0.3
Uniform distribution supports	$[\varphi_1, \varphi_2]$	$[0.10, 0.90]$
Wage setting $\Delta \bar{AB}$ weight	ψ_1	1
Wage setting Δcpi weight	ψ_2	0
Wage setting ΔU weight	ψ_3	0
R&D investment propensity	ν	0.02
R&D allocation to innovative search	ξ	0.5
Sensitivity of innovation success to R&D	o_{IN}	0.3
Sensitivity of innovation success to R&D	o_{IM}	0.3
Beta distribution parameters (innovation)	(α, β)	$(3, 3)$
Beta distribution support (innovation)	$[\xi_1, \xi_2]$	$[-0.10, 0.10]$
Radical innovation shift	χ^{RI}	0.025
New customer sample parameter	$\bar{\omega}$	0.5
Desired inventories	l	0.1
Payback period parameter	b	120
Logistic parameter for curve's steepness	η_1	1.5
Logistic value for sigmoid's midpoint	η_2	6
Sensitivity of interest on public bonds on debt to GDP ratio	ϱ	0.01
Inflation adjustment parameter	γ_π	1.10
Unemployment adjustment parameter	γ_U	1.10
Income tax rate	tax_i	0.1
Profit tax rate	tax_p	0.1
Unemployment subsidy rate	w^U	0.5

Sensitivity analysis

Here we perform a sensitivity analysis of the model's behaviour under direct innovation policies (Exp. IV and Exp. V) where we let vary one parameter at the time. All other parameters are set to their benchmark configuration (Table 8).

Table 9: Sensitivity analysis to key parameters. Values refer to averages across Monte Carlo experiments of size 50. # rad. inn. indicates the average number of successful radical innovations per run; GDP gr. and Unempl. stands for GDP growth and unemployment, respectively.

	Exp. IV				Exp. V			
	# rad. inn.	GDP gr.	Unempl.	Deficit	# rad. inn.	GDP gr.	Unempl.	Deficit
benchmark	0	3.40%	5.38%	5.17%	2.15	4.15%	5.37%	3.39%
η_1=1	0.02	3.41%	5.30%	5.10%	3.22	5.22%	3.82%	2.16%
η_1=1.2	0	3.40%	5.38%	5.17%	2.46	4.33%	4.45%	3.10%
η_1=2	0	3.40%	5.38%	5.17%	0.21	2.76%	6.83%	6.13%
η_2=4.5	0.16	3.47%	4.93%	5.02%	4.31	6.23%	3.67%	-2.47%
η_2=5	0.03	3.41%	5.35%	5.15%	3.58	5.72%	3.80%	-1.03%
η_2=7	0	3.40%	5.38%	5.17%	0.65	2.90%	6.24%	5.89%
ϱ=0.05	0	3.40%	5.38%	8.66%	2.15	4.15%	5.37%	4.71%
ϱ=0.1	0	3.40%	5.38%	10.34%	2.15	4.15%	5.37%	8.49%
ϱ=0.005	0	3.40%	5.38%	4.51%	2.15	4.15%	5.37%	3.08%
χ^{RI}	0.0125	3.40%	5.38%	5.17%	2.15	3.61%	6.01%	4.32%
χ^{RI}	0.05	3.40%	5.38%	5.17%	2.15	6.73%	2.93%	-2.88%