Mission-Oriented Policies and the "Entrepreneurial State" at Work: An Agent-Based Exploration *

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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.

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

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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 discounts). 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 path-breaking 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, 2018 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; Gräbner and Hornykewycz, 2022, the survey in Dawid, 2006 and the recent critical review by Aistleitner et al. (2021), wherein multiple modeling approaches are discussed). Indeed, we believe that a first-order systematic comparison between "Entrepreneurial State"-like policies and price-based R&D incentives is missing in literature linking macroeconomic dynamics and technical change, and it would be better carried out abstracting from choice of the particular sectors and missions to target (which is highly arbitrary and possibly affected by political considerations), though keeping vivid the spirit of

[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.

mission orientation (Mazzucato, 2013).

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, 2018, 2021) are also more effective at meeting uncontroversial innovation policy goals of productivity and growth gains.

2 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).[2] Our stylized representation 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.

2.1 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):

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

[2]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 climate and the economic growth (Lamperti et al., 2018, 2019, 2020, 2021).

Capital good firms adaptively strive to increase market shares and profits trying to improve their technology via innovation and imitation. These processes reflect the R&D activities performed by the firm. In line with Nelson and Winter (1982) and Nelson (1982b), we conceptualize R&D as a stochastic search process in which all firms in an industry face an identical distribution of outcomes. Both innovation and imitation are costly processes: firms invest in R&D a fraction of their past revenues in the attempt to implement incrementally new technologies, discover radically new innovations and imitate more advanced competitors.[3] Although these outcomes may differ across firms, all firms choose to undertake the same relative amount of R&D (Nelson, 1982b). In full agreement with this assumption, Coad and Rao (2010) find that "firms behave as if they aim for a roughly constant ratio of R&D to sales", thereby adjusting R&D expenditures to experienced sales growth.[4] Hence,

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

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

$$\theta_i^{IN}(t) = 1 - e^{-o_{IN} IN_i(t)}, \qquad o_{IN} > 0, \tag{5}$$
$$\theta_i^{IM}(t) = 1 - e^{-o_{IM} IM_i(t)}, \qquad o_{IM} > 0; \tag{6}$$

where the parameters $0 < -o_{IN}, o_{IM} \leqslant 1$ capture the the search capabilities fo 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:

$$A_{i,\tau+1} = A_{i,\tau}(1+\chi_{A,i}) \tag{7}$$
$$B_{i,\tau+1} = B_{i,\tau}(1+\chi_{B,i}) \tag{8}$$

where $\chi_{A,i}$ and $\chi_{B,i}$ are independent draws from a $Beta(\alpha,\beta)$ distribution over the support $[\xi_{1,i}, \xi_{2,i}]$, 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.

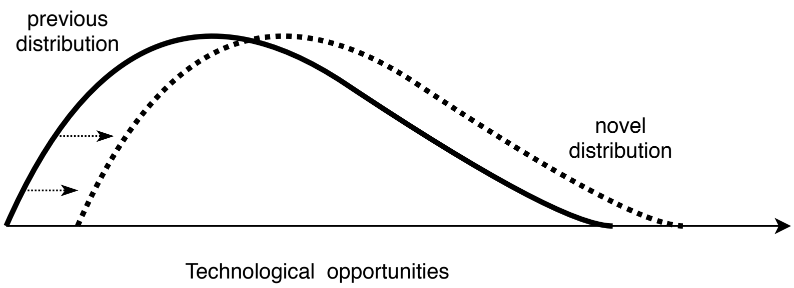
Successful imitators have the opportunity to copy the technology (embodied in the two technical coefficients A and B) of one of their competitors. The imitation probability negatively depends on the technological distance between each pair of firms. More precisely, the technological space is modelled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

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

[3] Of course, different modelling frameworks exist, for instance considering heterogeneous R&D intensities (e.g. Silverberg and Verspagen, 1994); we refer the reader to Dawid (2006) for a broader discussion.

[4] Empirical evidence on the manufacturing sector further suggests that, at the firm level, R&D spending is highly correlated with revenues, and that differences in R&D intensity (given by the ratio between R&D spending and revenues) can be largely explained by industry level characteristics, while factors as size and competition play a second-order role (e.g. Cohen et al., 1987).

Figure 1: Shift of technological opportunities implied by radical innovations



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, capital-good firms decide whether to adopt it or not by comparing its overall costs through the following routine:

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

where b is a payback parameter (more on that in Section 2.2), 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 available technology of vintage τ. Such routine guarantees that capital-good firms try to improve their competitiveness by manufacturing a machine that reduces the costs faced by their downstream clients. 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.

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). 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 at a given time (see also Figure 1):

$$\xi_{1,i}^{RI} = \xi_{1,i} + \chi^{RI}, \quad \xi_{2,i}^{RI} = \xi_{2,i} + \chi^{RI}, \tag{11}$$

where ξ^{RI} indicate the extrema of the support after a successful radical innovation.

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, $CRD_i(t) = \sum_{t^* < s \leq t} RD_i(s)$, proxies the stock of knowledge generated by the firm over time, after the eventual discovery, at time t^*, of a previous radical innovation. The probability (P_i^{RI}) that a capital-good firm i discovers a radical innovation enlarging the technological opportunities is then equal to:

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

with $\eta_1 > 0$ and $\eta_2 > 0$ controlling the shape of the logistic function.[5] 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). Further, our formulation is reminiscent of radical innovation resulting from exaptation, which suggests that firms may accumulate technological knowledge without anticipation of its subsequent uses, and a radically new technology may eventually emerge from deploying a firm's existing technological knowledge base into a new selection environment (see the special section edited by Andriani and Cattani, 2016). Indeed, enlarged technological opportunities diffuse through 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.

2.2 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. 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]

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.[7] 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_j 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:

$$\frac{p_j^{new}}{c_j^{con}(t) - c_j^{new}} \leq b \tag{14}$$

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.[8] 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: $I_j(t) = EI_j(t) + SI_j(t)$. Consumption-good firms sets the price of their final good

[5] Hence, the discovery of a radical innovation depends on the search effort exerted after another radical innovation had eventually been discovered. See also our discussion in Section 3.1.

[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.

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

[8] 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).

applying a variable mark-up on their 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.

For further details about the structure of the model please see Dosi et al. (2010).

3 Innovation policy experiments

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 3.1 first describes the different policy interventions, while simulation results are spelled out in Section 3.2.

3.1 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 (see Mazzucato, 2013 and the discussion in Castelnovo and Florio, 2020).

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 $q_{\mathrm{RD}} > 0$ are proportional to firm's past spending in research and innovation (RD_i):

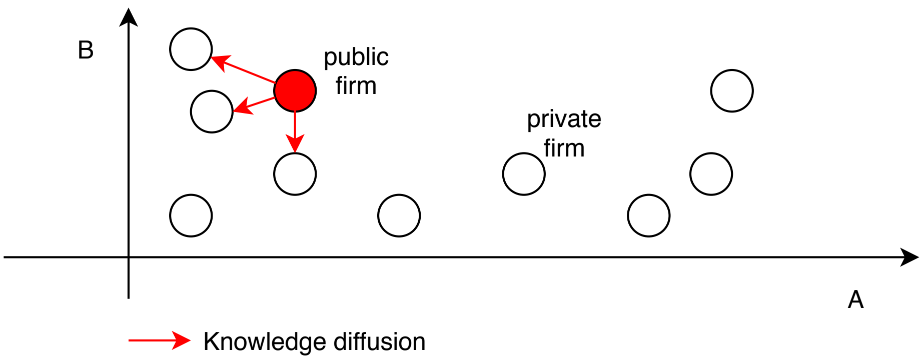
$$RD_i(t) = \upsilon S_i(t-1) + q_{\mathrm{RD}} RD_i(t-1). \tag{15}$$

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 firms pay a lower prices 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:

$$\frac{p^{new}(1-d_{TD})}{c_j^{con} - c^{new}} \leq b. \tag{16}$$

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 do not directly affect the innovation and investment decisions of firms, but they might increase productivity growth via more sustained levels of aggregate demand. In the model, consumption positively affects demand expectations and thus expansionary investment. This experiment may thus have, via this channel, a positive effect on R&D in the capital good sector,

Figure 2: Experiment IV: knowledge diffusion by the public firm



which depends on past sales. Nevertheless, its impact is expected to be lower compared to R&D subsidies and direct government innovation policies.

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). 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:

$$RD_{\text{pf}}(t) = \upsilon S_{pf}(t-1) + \Pi_{\text{pf}}(t-1) + IP(t). \tag{17}$$

Any capital-good firm 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 $\phi \in (0,1)$. However, a more distant firm may still imitate the public firm according to the process described in section 2.1. In general, we design Experiment IV to account for the role that public firms cover within Entrepreneurial State-like programs, in which they both contribute to the search process for novel technologies and further facilitate their diffusion (see Mazzucato, 2013; Nelson, 1982a; Chiang, 1991).[9] Figure 2 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 **??**), while bearing the risks and the costs of such ventures. In particular, 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 2.1). 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

[9] Consider, for example, the experiences of the Italian IRI and the French government-controlled electricity company EDF. See also Castelnovo and Florio (2020).

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):[10]

$$P_{NRL}^{RI}(t) = f\left(x \,|\, x = \frac{\sum_i CRD_i(t) + CRD_{\text{public}}(t)}{GDP(t)}\right) = \frac{1}{1+e^{\eta_1(x-\eta_2)}}. \tag{18}$$

Differently from private firms (see section 2.1), 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.[11] Further, we assume that the NRL leverages on the knowledge stock developed by the whole economy, while private firms on their internally developed technologies and those they master as a consequence of successful imitation. This reflects the difference between a research-oriented public organization and a private profit-driven firm (Mazzucato, 2013; Nelson, 1982a) and builds on the evidence that public agencies and laboratories have typically engaged in projects characterized by large technological breadth, merging pieces of technical knowledge developed across time by a number of public and private organizations (consider, for example, projects developed at the NASA and ARPA-E, as well as the experiences of mixed Bell labs or the Xerox Park; see also Mazzucato, 2013).[12]

Figure 3 exemplifies how cumulative R&D affects the discovery of a radical innovation by the NRL across multiple model runs. Indeed, as the economy-wide knowledge stock accumulates the probability of radical innovation increases logistically, according to equation 18. Contrarily, when cumulative R&D is relatively low, the likelihood of finding an innovation approaches zero which - in other words - implies that the NRL is not able to exploit the knowledge of the economy to enlarge the technological opportunities. When a radical innovation is discovered, the probability of finding a new one drops (panel B) and it re-starts increasing as long as additional R&D is performed, either publicly or privately.[13]

3.2 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 results of the model (see Table 1) 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

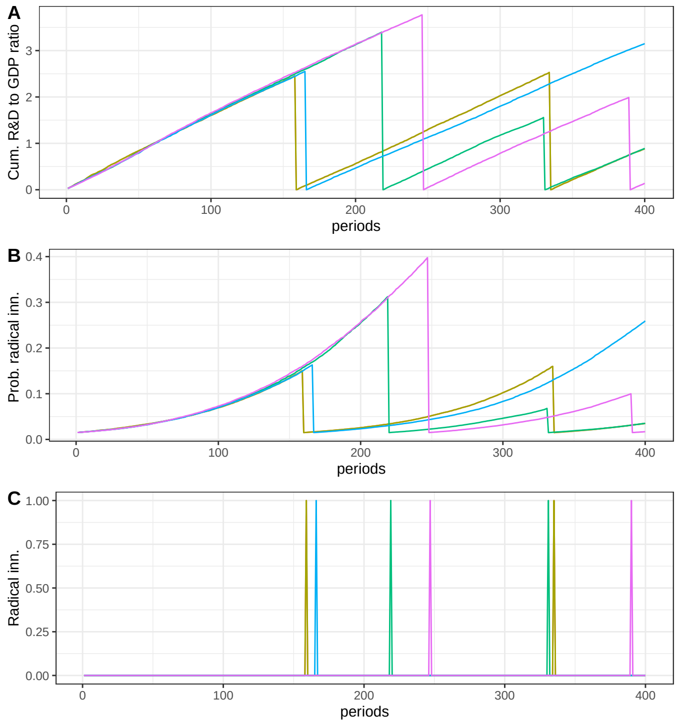
[10]To the contrary, the probability that private firms discover a radical innovation depends on own cumulative R&D and the R&D expenditures by the NRL, if any. See Equation 12.

[11]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 4).

[12] For example, the recent Cancer Moonshot program, largely coordinated by the NIH, collects research initiatives across a wide spectrum of scientific and technical fields, integrating and levering on knowledge stocks produced by several private and public firms, as well as universities and laboratories.

[13]This also indirectly reflects the idea that when missions are achieved, organizations often go through a phase of change wherein part of the knowledge stock is lost and needs being rebuilt towards new missions. For example, DeLong et al. (2004) reports "[...] to go to the moon again, we'll be starting from scratch. [...] in the 1990s NASA lost the knowledge it had developed to send astronauts to the moon. In an era of cost-cutting and downsizing, the engineers who designed the huge Saturn 5 rocket used to launch the lunar landing craft were encouraged to take early retirement from the space program".

Figure 3: Dynamic behavior of the cumulative R&D intensity between two successive radical innovations (x in Equation 18; panel A), probability that the NRL discovers a radical innovation (P^{RI}_{NRL}; panel B) and occurrence of a radical innovation (panel C) in Exp. V. Each line corresponds to a different model run.



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 2). 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 2).[14] 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 2. 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 discounts does not significantly improve neither output growth nor the employment rate with respect to the baseline, while R&D

[14]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.

Table 1: 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% *

subsidies do both.

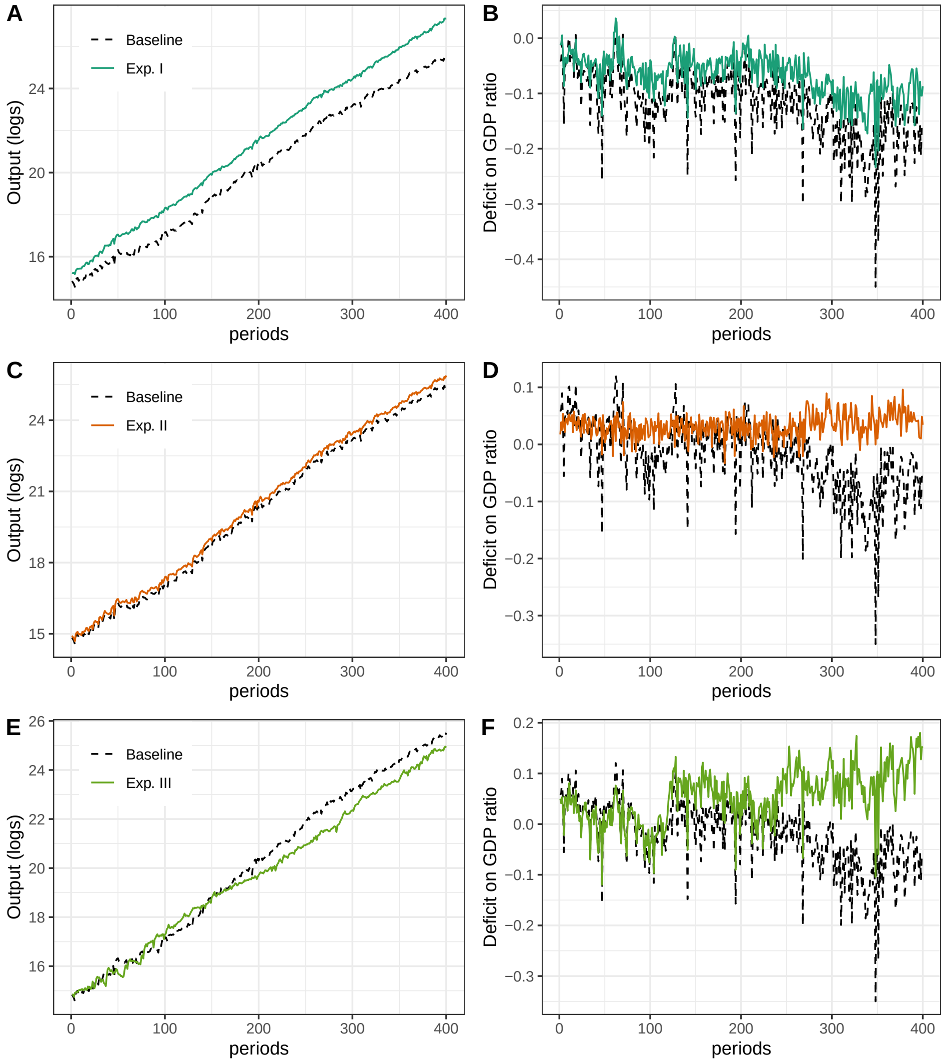
We also consider different pairs of innovation policies by equally splitting the public resources across the two interventions, thus guaranteeing comparability with previous (stand-alone) experiments. Simulation results reveals interesting synergies and redundancies across policies (see Table 2). First, 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 a mutually defeating effect of incentives to private firms in fostering innovation and growth. Indeed, by reducing public support both to technology discover (Exp. I) and downstream diffusion (Exp. II) such coupled policy turns out to be unsuccessful across both dimensions: reduced investment by consumption good firms both retard the penetration of novel technologies and decrease sales in the capital good sector, which in turn decreases future R&D spending. 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. The faster technological diffusion guaranteed by the presence of the public firm stimulates productivity and - hence - demand growth, which raise R&D spending (see also Tables 3 and 5 below) in the economy finally reducing the risks of failure of the NRL.

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 possibilities of the economy.[15] 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 has relatively higher chances to introduce radical innovations, which shifts to the right the entire distribution of technological, and thus growth, opportunities, with respect to private firms. 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 3 allows one to better understand the microeconomic drivers of hysteresis in our simulation experiments.

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

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.



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 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 3), 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 2.1). Simulation runs wherein the private firms are able to quickly catch-up the public one display - ceteris paribus - higher productivity growth (Figure 8). These

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.

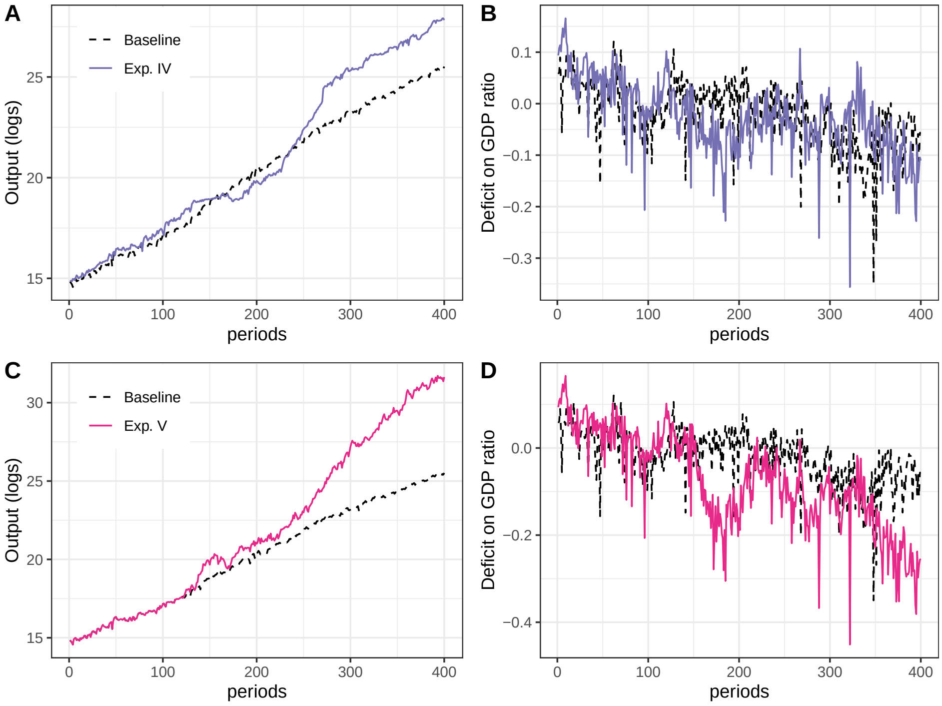
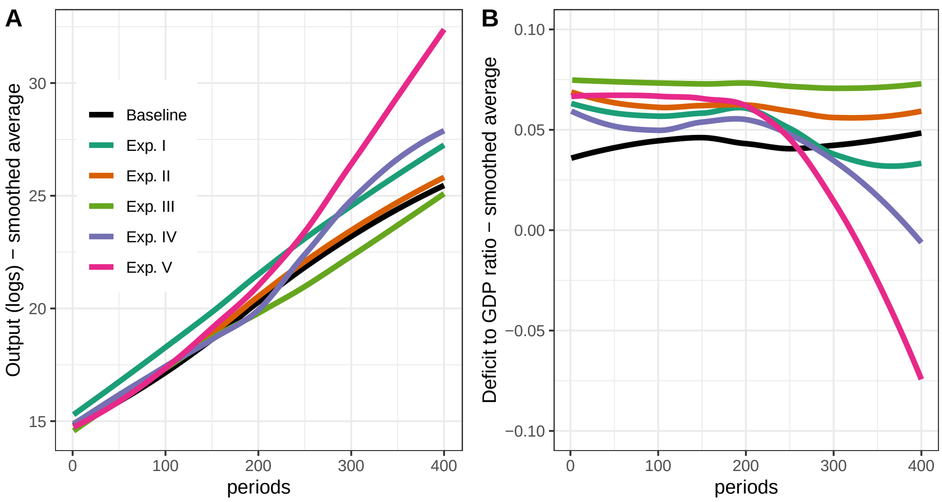


Figure 6: Dynamics of GDP (panel A) and public deficit (panel B) across experiments. Averages over 200 Monte Carlo runs. Exp. I: R&D subsidies; Exp. II: Investment tax discount; Exp. III: Transfers to consumption; Exp. IV: Public firm; Exp. V: National Research Lab.



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

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.

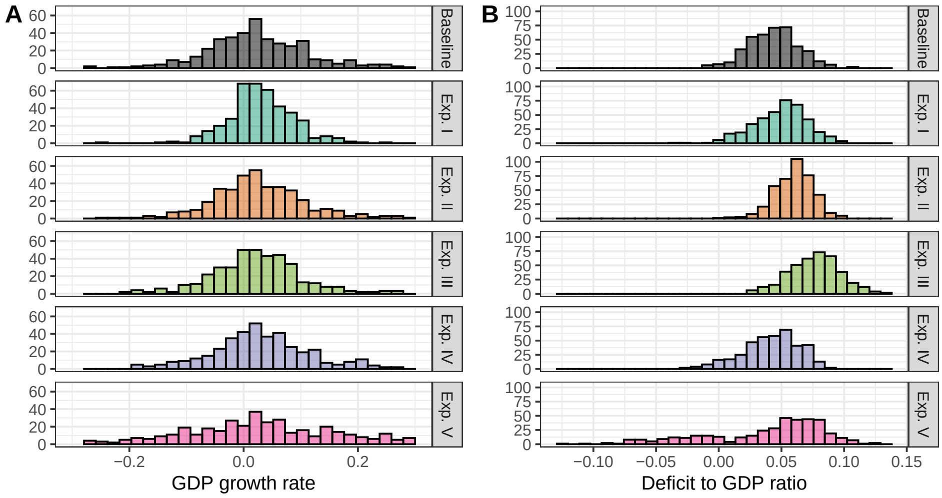
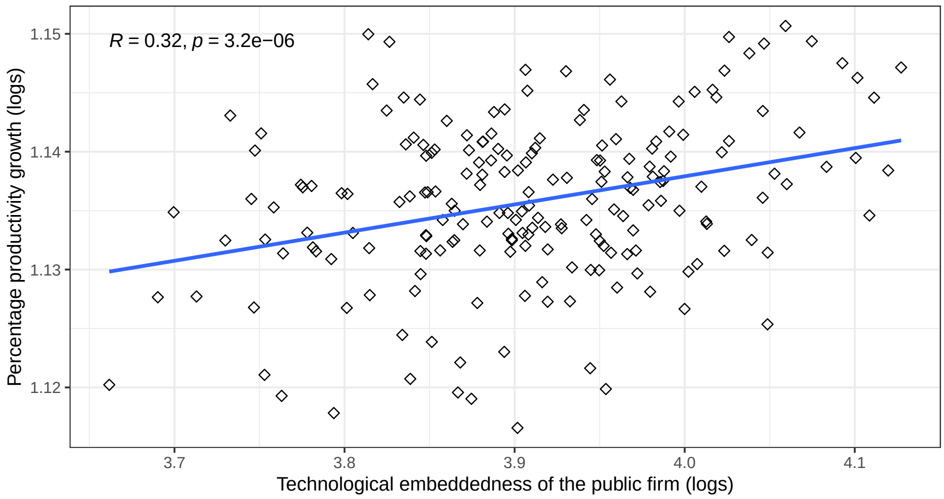


Figure 8: Technological embeddedness of the public firm and aggregate productivity growth in the economy under Experiment IV (Public firm). Each point represents the average over a Monte Carlo run; 200 runs are used.



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). While experiments from I to III display a rather homogeneous behavior across runs (see the distributions of Figure 7), Exp. V and VI induce a trade-off between superior average growth performance and higher risks of policy failures. Indeed, simulation results clearly reveal the perils of Entrepreneurial State policies wherein for every winning investment there are many possible failures (Mazzucato, 2016).[16] 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

[16]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.

Table 2: 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*

Exp. V, the public R&D 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). The status of public finances differs sharply across experiments (see, e.g. Figure 6). Indirect innovation policies (Exp. I and II) and transfers to consumption increase the deficit to GDP ratio of the economy with respect to the baseline, as the additional growth they eventually generate does not fully compensate for the cost of the policy itself. However, the government incurs in a stable series of deficits both over time and across runs (see Figure 7, signaling relatively low risks from these policy scenarios. Differently, direct innovation policies (Exp. IV and, especially, V) induce an initial phase of deficit, which gradually improves over time as the knowledge stock of the economy increases and the policies get efficacy boosting output growth and fiscal revenues. However, failures of the Entrepreneurial State could impede such a shift in the stream of deficits, making Exp. IV and V comparatively riskier.

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'

Table 3: 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

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.

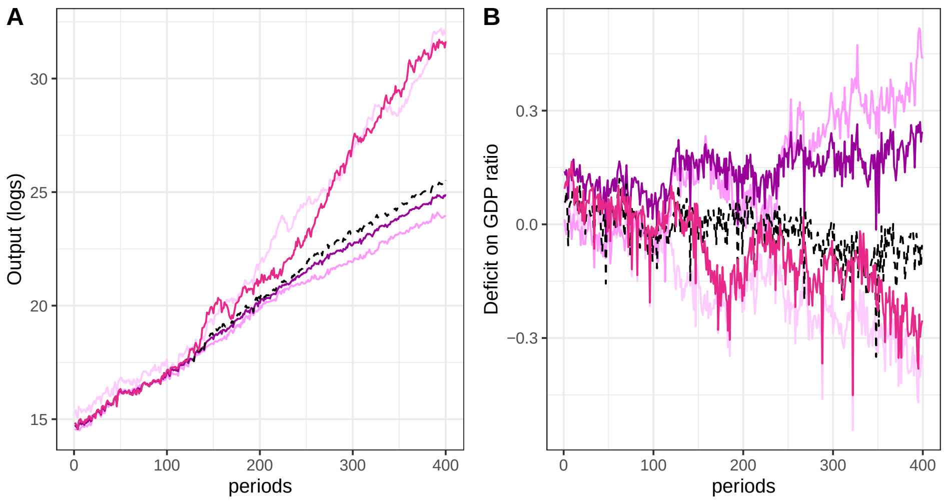


Figure 10: Status of public finances under Experiment V (National Research Lab); panel A reports the distribution of simulation-average deficits and panel B the distribution of simulation-average debt; 200 runs are used. The blue line indicates the mean while the dashed red line crosses the x-axis at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

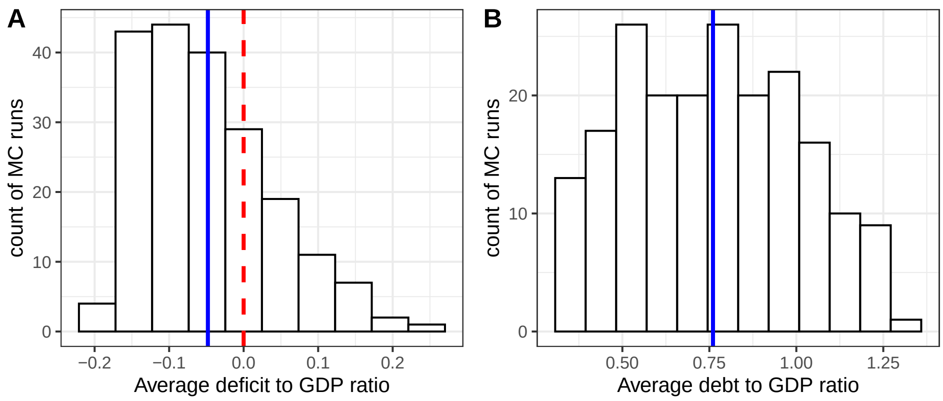


Table 4: Crowding-in of private investments in R&D. Each column reports the estimates of Equation (19) using data relative to different experiments; 200 Monte Carlo runs are employed. Exp. I: R&D subsidies; Exp. II: Investment tax discount; Exp. III: Transfers to consumption; Exp. IV: Public firm; Exp. 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 5: Crowding-in of private investments in R&D. Each column reports the estimates of Equation (19) 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

R&D investment, by performing OLS regressions on the artificial data generated by different policy experiments:[17]

$$\log RD_{i,s,t} = \beta_1 \log IP_{s,t-1} + \beta_2 \log GDP_{s,t-1} + \lambda_i + \mu_s + \nu_t + \varepsilon_{i,s,t} \tag{19}$$

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 4 and 5). 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.

4 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.

[17] Our artificial economy offers a convenient setting to estimate Equation (19) 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.

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.

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