Journal of Economic Dynamics & Control 151 (2023) 104650

Contents lists available at ScienceDirect

Journal of Economic Dynamics & Control

journal homepage: www.elsevier.com/locate/jedc

Mission-oriented policies and the "Entrepreneurial State" at work: An agent-based exploration

Giovanni Dosi[a], Francesco Lamperti[a,b,*], Mariana Mazzucato[c], Mauro Napoletano[d,e,f], Andrea Roventini[a,e]

[a] Institute of Economics and EMbeDS, Scuola Superiore Sant'Anna, Pisa, Italy
[b] RFF-CMCC European Institute on Economics and the Environment, Milan, Italy
[c] Institute for Public Purpose and Policy, University College London London, UK
[d] Université Côte D'Azur, CNRS, GREDEG, France
[e] Sciences Po, OFCE, France
[f] Scuola Superiore Sant'Anna, Pisa, Italy

ARTICLE INFO

Article history:
Received 6 August 2021
Revised 16 December 2022
Accepted 26 March 2023
Available online 30 March 2023

JEL classification:
O33
O38
O31
O40
C63

Keywords:
Innovation policy
Mission-oriented R&D
Entrepreneurial state
Agent-based modelling

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.

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

* Corresponding author at: Institute of Economics, Scuola Superiore Sant'Anna, piazza Martiri della Libertà 33, 56127 Pisa, Italy.
E-mail addresses: g.dosi@santannapisa.it (G. Dosi), f.lamperti@santannapisa.it (F. Lamperti), m.mazzucato@ucl.ac.uk (M. Mazzucato), mauro.napoletano@univ-cotedazur.fr (M. Napoletano), a.roventini@santannapisa.it (A. Roventini).

https://doi.org/10.1016/j.jedc.2023.104650
0165-1889/

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 Criscuolo et al., 2020; Edler and Fagerberg, 2017; Freeman and Soete, 1997). 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, 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 via their stimulus to incremental and radical innovation, 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 Caiani et al., 2019; Dawid et al., 2008; Dosi et al., 2019; Fagiolo et al., 2020; Gräbner and Hornykewycz, 2022; Lorentz et al., 2016; Russo et al., 2007, 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 the 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 mission orientation (Mazzucato, 2013).

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 counter-factual analyses. We examine four stylized 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

[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 Dawid and Delli Gatti (2018); Dosi and Roventini (2019); Fagiolo and Roventini (2017). We also suggest to look at Dosi et al. (2020c) for a systematic comparison of market-based and industrial policies in fostering catching-up.

opportunities available in the economy. The first two experiments mimic indirect innovation policies, while the latter pair captures key features of direct or "Entrepreneurial-State" policies, leaving aside the decision of which mission(s) to target. Finally, we consider a benchmark scenario where the public resources is 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* (Cerra et al., 2021; Dosi et al., 2018) 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 (Aghion and Howitt, 1992; Romer, 1986; Solow, 1957) and evolutionary theories (Dosi, 1982; Dosi et al., 1994; Nelson and Winter, 1982). 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 (Gross and Sampat, 2020; Moretti et al., 2019). But what motivates innovation policies themselves?[2]

The *market view* closely based on a neoclassical perspective justifies policies with the presence of market failures or untraded externalities. Building on these premises, innovation policies should be designed as monetary incentives aligning private behaviors and delivering the socially optimal level of innovation. This implicitly shrinking the scope for a more active role of the State in shaping the technological landscape. Indeed, 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 private actors' incentives to innovate and social objectives - which overstretches the implications 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. Though appealing as they are for their simplicity and highly influential among policy makers (EU, 2020; OECD, 2010) and economists alike, these arguments build on weak foundations and - we argue - should not limit the innovation policy debate to the design of tax credits, subsidies and IPRs (see, e.g., Bloom et al., 2019; Guellec and Van Pottelsberghe De La Potterie, 2003).

On the theoretical side, the focus on market-based instruments to conduct innovation policy is postulated on the role general equilibrium effects under "complete markets". However, there is a fundamental incompatibility between innovation and general equilibrium, basically for two reasons (Cimoli et al., 2009; Stiglitz, 1996). 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

[2] The interested reader can find critical surveys of innovation policy instruments in Bloom et al. (2019); Borrás and Edquist (2013); Edler and Fagerberg (2017) and Mazzucato (2016).

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. Further, 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 (Dosi, 1988; Dosi and Nelson, 2010; Metcalfe, 2005; Nelson and Winter, 1982; Polanyi, 1944; Winter, 1998).

More generally, the empirical evidence supporting any link between incentives and the propensity to generate or acquire knowledge is at best fuzzy. First, the available evidence backing the effectiveness of monetary subsidies and stronger IPR regimes to stimulate private R&D spending is rather weak (Dimos and Pugh, 2016; Papageorgiadis and Sharma, 2016; Zúñiga Vicente et al., 2014), 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 (Cimoli et al., 2014; Dosi et al., 2006; Dosi and Stiglitz, 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 hardly 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). Indirectly, the scope for active, direct innovation policies is further justified by a recent stream of studies suggesting that long-term growth is facilitated by the development of *complex products*, i.e. tradable artifacts closely related to many economic activities (Hidalgo et al., 2007; Tacchella et al., 2012), to which innovation policies might aim at, given the locally available technological competences. 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).

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. Along these lines, public policies should 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 (Bloom et al., 2019), being them 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). A recent assessment of the US moonshot program implemented during the 1960s finds large, first order and long lasting growth effects induced by public R&D conducted through the NASA (Kantor and Whalley, 2022). However, novel opportunities come together with additional risks, and it is not automatic that missions-oriented programs translate into success stories; to the contrary, for every winning mission-oriented investment there are many possible failures (Mazzucato, 2016). The ultimate result likely depends both on the uncontrollable uncertainty of the search process itself (Dosi, 1988) - which may well reveals unsuccessful - and on the politically controllable willingness of the government to sustain eventual costs and losses during the research path.

The historical record provides compelling cases in support of Entrepreneurial State interventions. 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; Gross and Sampat, 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). To the contrary, failed missions exist and the literature's focus on case studies has often tended to highlight successes and provide too few examples of failures, which may lead to overstate the positive consequences and downplay the negative effects of mission-oriented R&D programs (Mowery, 2010). Indeed, dramatic flops have been reported for energy, defense and aerospace related programs (Mazzucato, 2016; Mowery, 2010; Nelson, 1982a). Even though it is empirically difficult to balance the economic significance of failures against successes, often because of missing counterfactual cases (Mowery, 2010), this paper attempts at contributing to such assessment by means of a simulation laboratory.

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.[3] 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 (Edquist, 2011; Metcalfe, 1994; 1995).

3. The K+S model

We compare a variety of innovation policies and their economy-wide effects in the Schumpeter meeting Keynes model extended to account for radical innovations and the variable cost of public debt (Dosi et al., 2013; 2010).[4] 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.

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. 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.[5] Although these outcomes may differ across firms, all firms choose to undertake the

[3] 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.

[4] See also Dosi et al. (2017a) 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, 2022) and the coupled dynamics of climate climate and the economic growth (Lamperti et al., 2019; 2021; 2018a; 2020).

[5] 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.

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.[6] 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:

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

In the Appendix, we test the robustness of our findings with respect to alternative routines describing a firm' R&D spending decision, in particular allowing search intensity to depend on the (i) relative size of its innovation effort (Cohen and Klepper, 1992) and (ii) the sign of the growth previously experienced (Coad and Rao, 2010). 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 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:

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

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

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:

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

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 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 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 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 Block and Keller, 2015; Mowery, 2010 and the discussion in Section 2). To capture these features, we model radical innovations as shifts of the

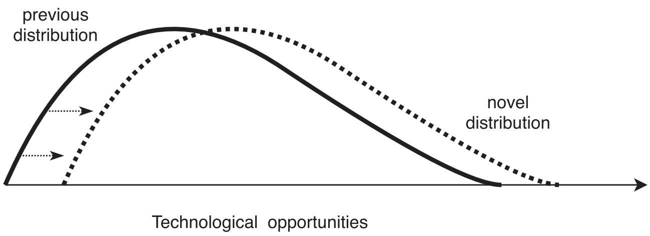

Fig. 1. Shift of technological opportunities implied by radical innovations.

support $[\xi_1, \xi_2]$ of the distribution of technological opportunities available to the firm at a given time (see also Fig. 1):

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

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.[7] 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 (Dunlap-Hinkler et al., 2010; Kaplan and Vakili, 2015; Phene et al., 2006). 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.

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. 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.[8]

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.[9] 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

[6] 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).

[7] 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 5.1.

[8] 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.

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

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.[10] The vintages of machines that satisfies Eq. 14 constitute the replacement investment of the firm, $SI_j(t)$. Aggregate investment, in monetary terms, just sums over the value of investments of all consumption good firms:

$$I(t) = \sum_j [EI_j(t) + SI_j(t)] p_j(t), \tag{15}$$

where $p_j(t)$ is the price of a new machine available to firm j at time t.

Consumption-good firms sets the price of their final good 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.[11]

At the end of each period, consumption-good and capital-good firms compute their profits and update their stock of liquid assets. As in Dosi et al. (2010), firms finance production using internal funds and, if the latter are not sufficient - they borrow from credit lines, over which they pay a constant interest rate, up to a maximum debt to revenues ratio. 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:

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

where w represent wages, w^U the unemployment subsidy and L^D and L^S labour demand and labour supply respectively. Aggregate labor demand is computed summing up the labor demands of capital- and consumption-good firms; labor supply is exogenous and inelastic, as in Dosi et al. (2010). Wages are linked to the dynamics of productivity, prices and unemployment rate by the following wage equation:

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

where $\bar{AB}$ 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 run innovation policy incurring in additional spending as indicated by IP (more on that in Section 5). The deficit is then equal to:

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

[10] 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. Eisner, 1972; Feldstein and Foot, 1971; Goolsbee, 1998).

[11] Unfilled demand is due to the difference between expected and actual demand. Firms set their production according to the expected demand. If a firms 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.

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:

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

with $\varrho > 0$. Indeed, public debt is implicitly placed within a external international financial market charging higher interest rates in presence of larger stock of debt. 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.[12]

Finally, the model satisfies the standard national account identities: the sum of value added of capital- and consumption goods firms equals aggregate production (in our simplified economy there are no intermediate goods). In turns, the value of total output coincides with the sum of aggregate consumption, investment and change in inventories:

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

where Q_i and Q_j represent the production of capital and consumption good firms, respectively, p_i and p_j^c the prices charged by capital and consumption good firms, while C, I and ΔN stand for consumption, investment and the variation of inventories, all measured in nominal terms. The real stance of each aggregate variable can be obtained dividing by the appropriate deflator (CPI for aggregate consumption and inventories; PPI for investments), and the real GDP simply corresponds to their sum.[13]

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 Fagiolo et al., 2019; Fagiolo and Roventini, 2017; Windrum et al., 2007). In what follows, we therefore perform extensive Monte-Carlo analyses to appropriately account for cross-simulation variability. More precisely, all results are presented either as single simulation runs, to show the behaviour of our artificial economy along an 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 validated" the model, i.e. we studied its capability to account for a large ensemble of macro and micro stylized facts (see Fagiolo et al., 2019; Windrum et al., 2007)[14]

In particular, the parameter space has been extensively explored (through random sampling and in absence of innovation policy) in search of the three properties listed below. Then, a best candidate vector of parameters has been retained (see the Appendix for the list of parameters) and - finally - a series of validation tests based on stylized facts (i.e. known empirical regularities) replication 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).[15] That said, we stress that our exercises should be taken much more as thought experiments aimed at unveiling mechanisms, comparing policies and establishing robust rankings, rather than delivering quantitative predictions. Table 1 shows the stylized facts that the model replicates.[16]

Fig. 2 shows the dynamics of the model in the "no innovation policy" baseline relying on a single model run, while Table 2 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.

[12] 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). Further, we check that debt to GDP ratios remain under control (below 150%) in all simulations.

[13] Thanks to the micro-founded nature of the model we are able to collect the prices charged and the quantities produced by each firm in each sector, which - in turns - give the consumption price index (CPI) and the producer price index (PPI). The prices charged by consumption good firms (p_j^c) correspond to a markup over production costs, see Dosi et al. (2010) for details.

[14] See also Lamperti (2018a,b), Guerini and Moneta (2017) and Lamperti et al. (2018c). By indirect calibration we refer to an algorithmic procedure wherein a set of empirical properties is targeted, a parameter vector satisfying them is obtained and the replication of a larger set of stylized facts is examined.

[15] 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.

[16] We point the reader to Dosi et al. (2017a) 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.

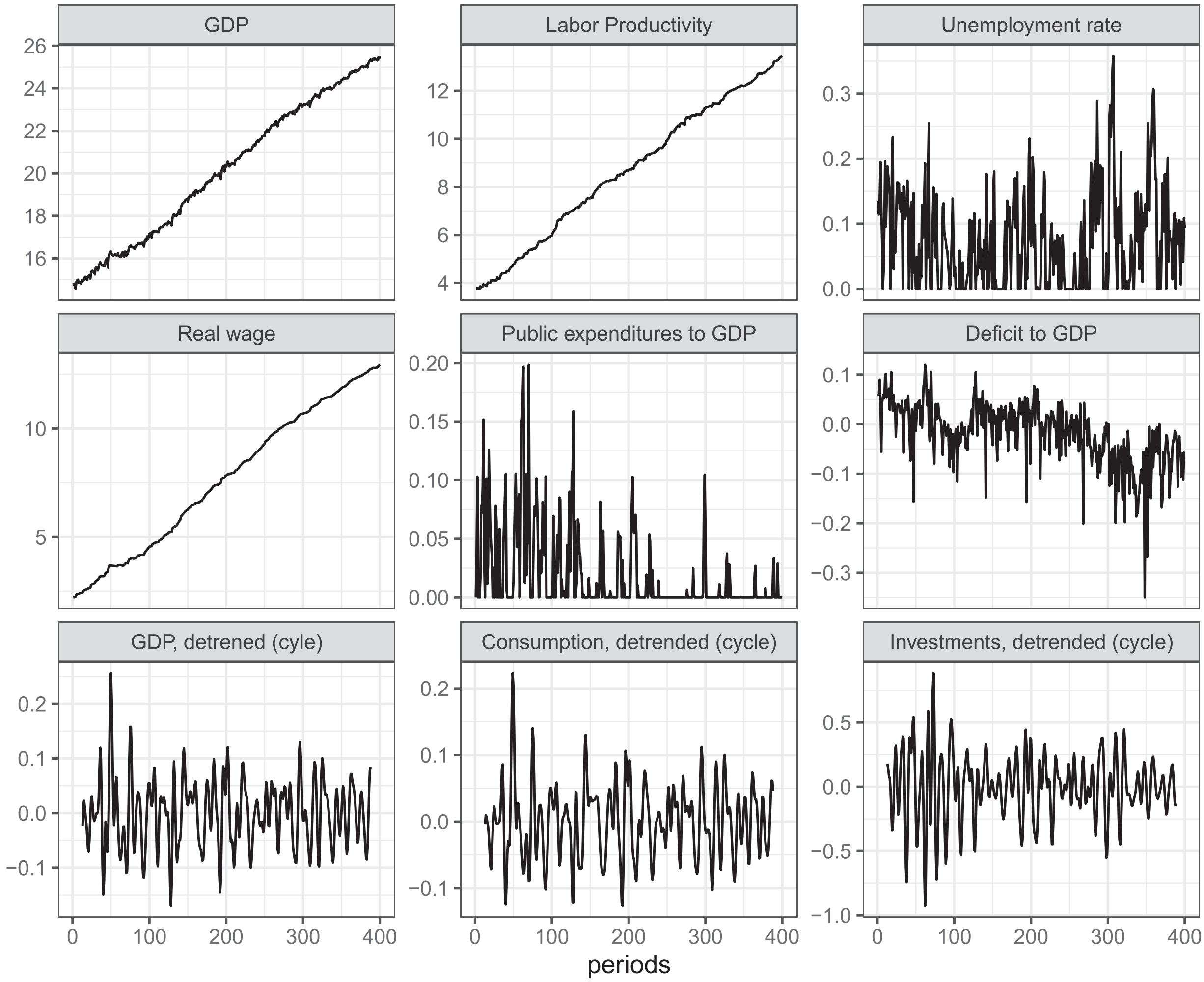

Fig. 2. Model behaviour under the "no innovation policy" baseline. Selected indicators are reported for a single model run. GDP, Labour productivity, Real wage are in logs. Negative public deficit indicates a surplus.

Table 1
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) Stock and Watson (1999); Zarnowitz (1985)
SF2 Fat-tailed GDP growth-rate distribution	Castaldi and Dosi (2009); Fagiolo et al. (2008) Lamperti and Mattei (2018)
SF3 Recession duration exponentially distributed	Ausloos et al. (2004); Wright (2005)
SF4 Relative volatility of GDP, consumption and investments	Napoletano et al. (2006); Stock and Watson (1999)
SF5 Cross-correlations of macro variables	Napoletano et al. (2006); Stock and Watson (1999)
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)

Table 2
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	0.0258	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

Table 3
Results from Experiment 1 (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.

Baseline	GDP growth 2.68%	GDP vol. 0.08	Unempl. 6.10%	Periods full empl. 16%	Deficit 4.34%	Fiscal cost 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% *

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 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 Fig. 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 (Napoletano et al., 2006; Stock and Watson, 1999).

As mentioned above (see Table 1), the baseline configuration of the K+S model is able to account for a wide set of microeconomic empirical regularities concerning e.g. firm size and growth-rate distributions, productivity dynamics, investment patterns; see also Dosi et al. (2017a) for additional details. This reflects the strong explanatory capabilities of agent-based models as discussed in Haldane and Turrell (2019) and Dosi and Roventini (2019).

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 2 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), together with a set of additional experiments (see Tables 10, 11 and 12) where we test alternative designs of the policy interventions described below, as well as alternative behavioural assumptions.

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 1 and 2 consider indirect policy interventions typical of the *market failure* approach, whereas Experiments 4 and 5 explore direct Government interventions and are akin to the *Entrepreneurial State* framework (see Mazzucato, 2013 and the discussion in Castelnovo and Florio, 2020).[17] As an additional benchmark, we consider a scenario (Experiment 3) where public expenditures sustain only private consumption and hence cannot have a direct influence on productivity growth.

Experiment 1. (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):

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

Experiment 2. (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:

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

Experiment 3. (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, which depends on past sales. Nevertheless, its impact is expected to be lower compared to R&D subsidies and direct government innovation policies.

Experiment 4. (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 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 $\phi \in (0,1)$. In other words, the public firm discloses the blueprints of its technology to private firms that are sufficiently close from a technological perspective. In turn, private firms can decide to use the public firm's blueprints, if convenient (i.e. using the same routine described by equation (10)). However, a more technologically distant firm may still imitate the public firm according to the process described in Section 3.1. In general, we design Experiment 4 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 Chiang, 1991; Mazzucato, 2013; Nelson, 1982a).[18] Fig. 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 Eq. (10).

Experiment 5. (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, 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,

[17] In the Appendix, we test the robustness of such policies to various alternative assumptions.

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

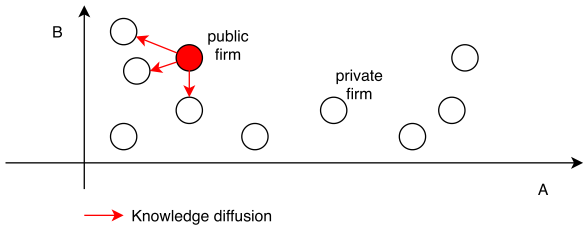

Fig. 3. Experiment 4 : knowledge diffusion by the public firm.

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):

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

Equations (24) and (12) reveal a clear asymmetry between the NRL and private firms. In particular, in the search for radical innovations, the NRL leverages the knowledge stock developed by the whole economy; differently, capital-good firms build on own and public cumulative R&D, but not on the knowledge stock developed by other private firms. Such an assumption is meant to reflect the difference between a research-oriented public organization and a profit-driven private firm (Mazzucato, 2013; Nelson, 1982a), and is grounded on the historical 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 and Kantor and Whalley, 2022).[19] However, the ability of the NRL to exploit the existing body of knowledge is not perfect, in the sense that additional R&D activities just raise the probability of finding a radical innovation, but they never guarantee such a discovery.

Further, 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.[20] This is another difference between the NRL and private capital-good firms (see Section 3.1).

Fig. 4 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 Eq. 24. 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.[21]

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 1 (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 3) 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 $IP(t) = 0.026 \cdot GDP(t)$.

Single innovation policies. Figs. 5 and 6 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

[19] 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.

[20] 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).

[21] 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".

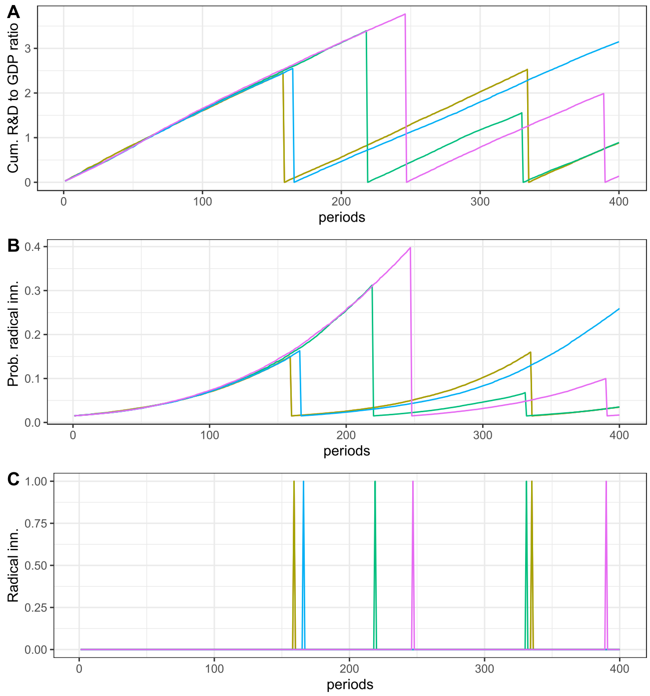

Fig. 4. Dynamic behavior of the cumulative R&D intensity between two successive radical innovations (x in Eq. 24; panel A), probability that the NRL discovers a radical innovation (P^{RI}_{NRL}; panel B) and occurrence of a radical innovation (panel C) in Exp. V. Each line corresponds to a different model run..

Table 4
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*

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 Figs. 7 and 8), 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 Fig. 6).

Further, direct intervention policies are more effective than indirect ones as far as 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 Fig. 8 and Table 4). 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 4).[22] Decreasing deficits-to-GDP

[22] 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.

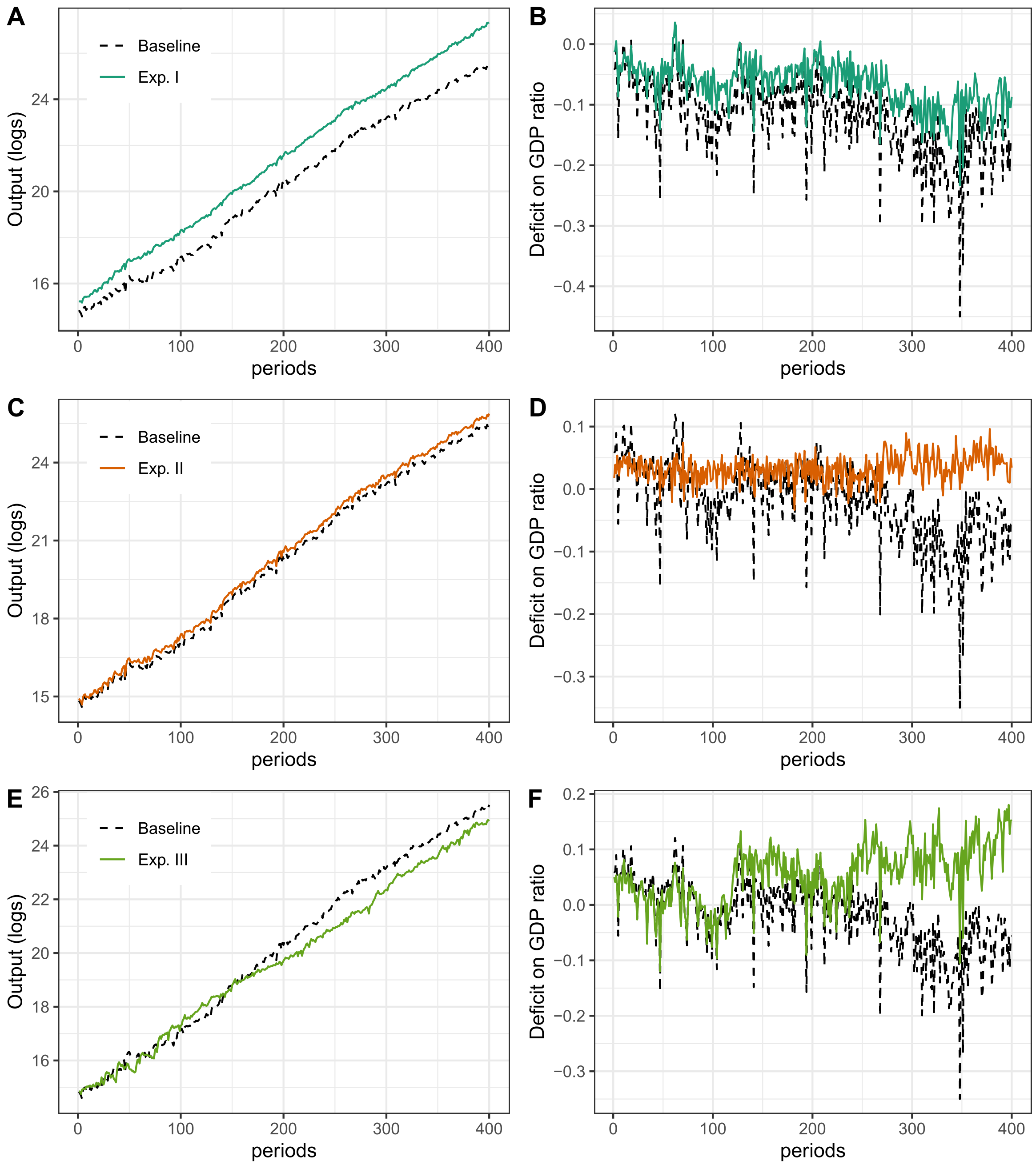

Fig. 5. Dynamics of GDP and public deficit across experiments for indirect innovation policies. Each row of panels corresponds to an experiment: panels A and B to Experiment 1 (R&D subsidies), panels C and D to experiment II (Investment tax discount), panels E and F to experiment III (Transfers to consumption). Each plot shows a single model run under the experiment and the "no innovation policy" baseline.

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 4. The battery of Monte Carlo statistics shows in particular that Experiment 5 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 4 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. Indi-

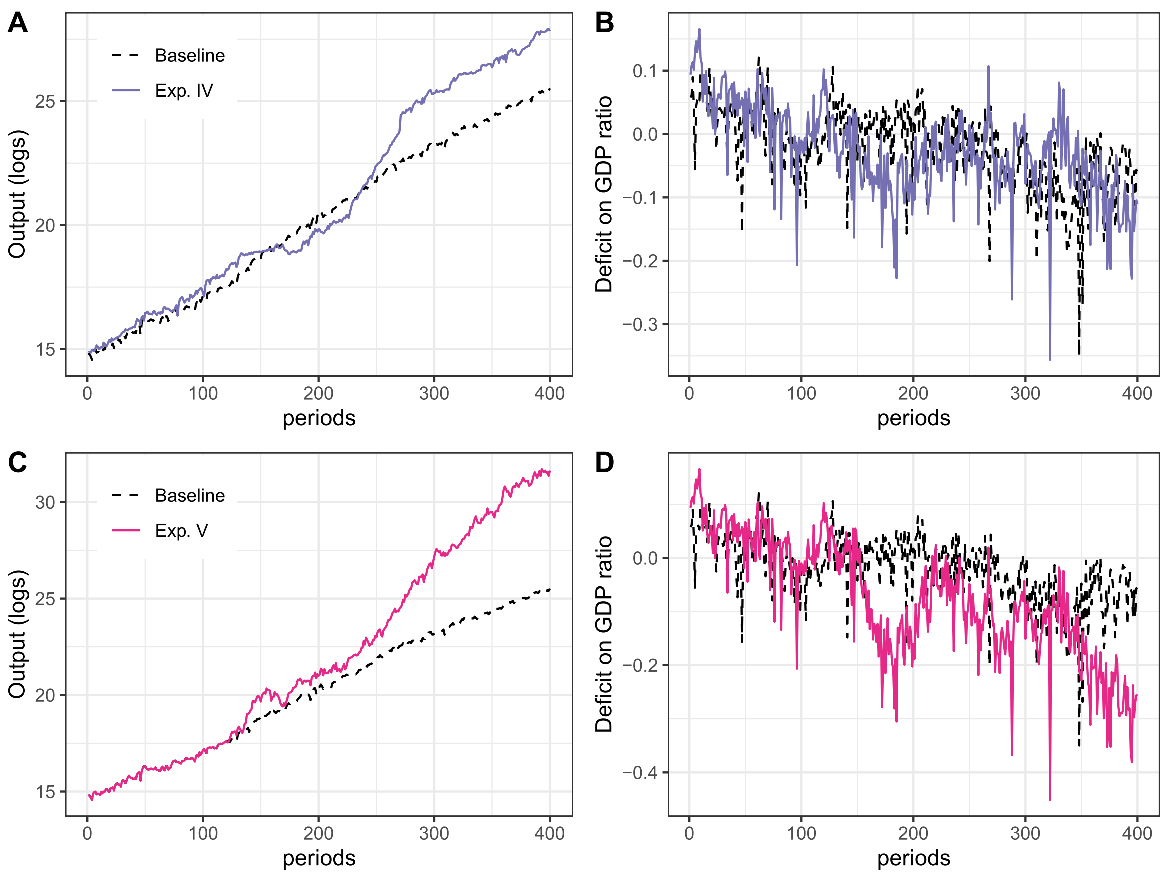

Fig. 6. Dynamics of GDP and public deficit across experiments for direct innovation policies. Each row of panels corresponds to an experiment: panels A and B to Experiment 4 (Public firm) and panels C and D to experiment V (National Research Lab). Each plot shows a single model run under the experiment and the "no innovation policy" baseline.

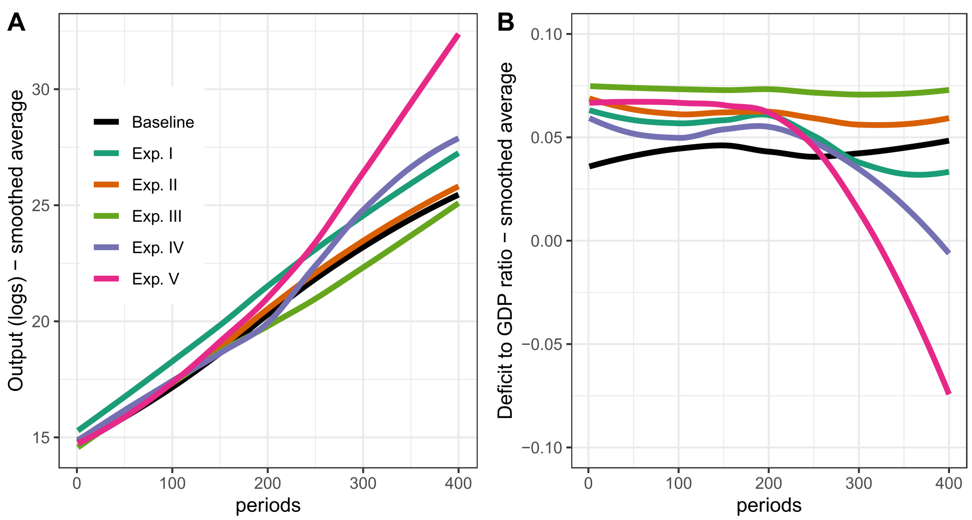

Fig. 7. Dynamics of GDP (panel A) and public deficit (panel B) across experiments. Averages over 200 Monte Carlo runs. Exp. I: R&D subsidies; Exp. II: Investment tax discount; Exp. III: Transfers to consumption; Exp. IV: Public firm; Exp. V: National Research Lab.

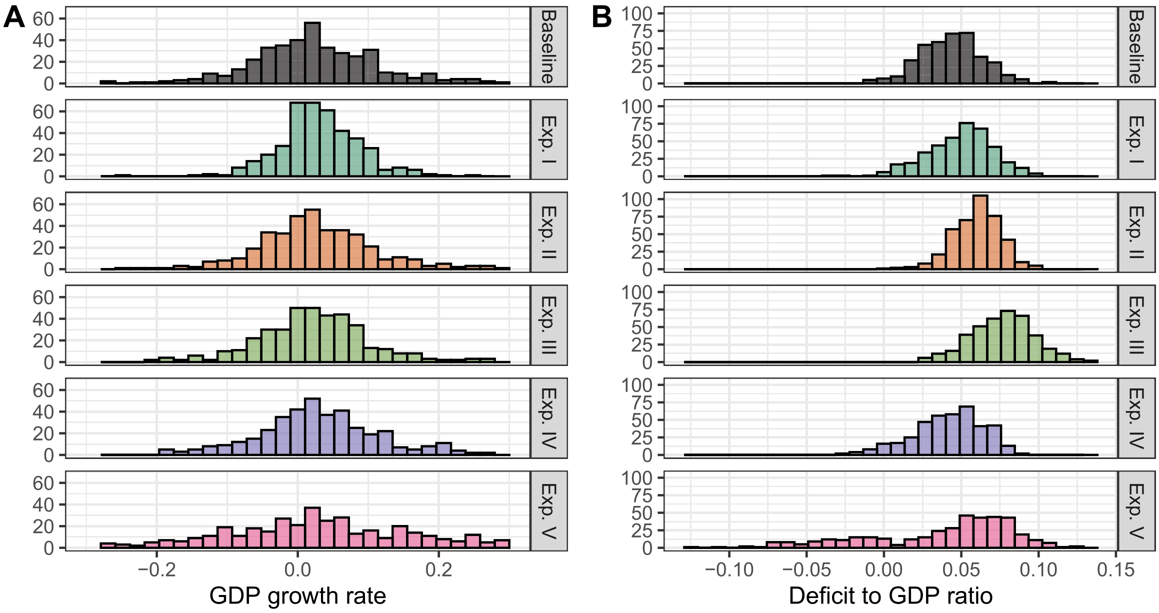

Fig. 8. Distribution of GDP growth (panel A) and public deficit (panel B) values across experiments. Pooling of averages over 200 Monte Carlo runs, each observation corresponds to the Monte Carlo average in a given simulation step. Exp. I: R&D subsidies; Exp. II: Investment tax discount; Exp. III: Transfers to consumption; Exp. IV: Public firm; Exp. V: National Research Lab.

rect innovation policies (Exps. I and II) are more effective to stimulate productivity and GDP growth in the short-run (Fig. 7), 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 subsidies do both. However, we show in the Appendix (see Table 10) that tax credits on R&D - and not on physical investments - prove superior to Exp. I under the assumption that firms anticipate the policy and raise their search efforts accordingly. Such effect is driven by R&D credits guaranteeing higher liquid resources to firms, which cushion against downswings of the cycle. As expected, public transfers to consumption ranks last with a negative impact on GDP growth and public deficit (but lower average unemployment rate). A number of additional tests are collected in the Appendix. Tables 9 and 12 show the robustness of Exp. V's superior performance against a number of alternative specifications. Interestingly, we run a scenario in which the discovery of radical innovations depends solely on the R&D conducted within the organization. In this setting the NRL is way less effective at stimulating growth than in the standard Exp. V, which points to the importance of building public laboratories that effectively leverage on private R&D. In particular, the NRL achieves - on average - less than one radical innovation per run (0.96; Table 12), which should be compared to the 2.15 radical innovations per run of the standard experiment (see also Table 9). Intuitively, this translates in a trajectory characterized by sustained yet lower growth, reduced volatility and slightly larger deficit. Nevertheless, even in this modified experiment, the NRL policy emerges as comparatively superior - on average - to other innovation policies (Table 4). Finally, Table 11 shows that our ranking of innovation policies is robust to alternative specifications of the routine used by capital-good firms to invest in R&D, though some quantitative differences emerge.

Combinations of innovation policies. 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 4). 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 1 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 1 and 2 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 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 5 and 7 below) in the economy finally reducing the risks of failure of the NRL.

Table 5
Experiment 4 : 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

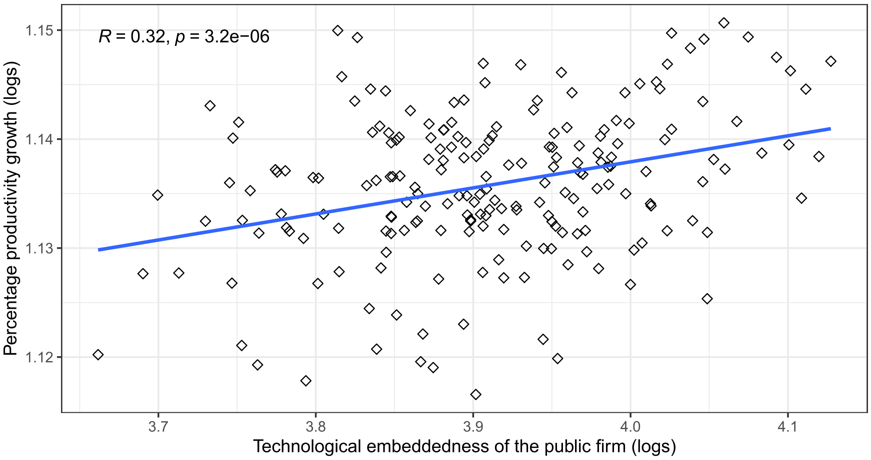

Fig. 9. Technological embeddedness of the public firm and aggregate productivity growth in the economy under Experiment 4 (Public firm). Each point represents the average over a Monte Carlo run; 200 runs are used.

Positive hysteresis. 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.[23] 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. Table 9 (in the Appendix) reports the share of runs with at least one radical innovation, which is the ultimate responsible for the change of paradigm in the growth dynamics. Thus, while almost all hysteresis literature focuses on the long-lasting impact of recessionary shocks on employment and GDP (see e.g., Cerra et al., 2021; Dosi et al., 2018), our results show that Entrepreneurial State innovation policies can positively affect the growing possibility of the economy.

Table 5 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 Fig. 6. However, this process eventually stops (see panel C of Fig. 6 and panel B of Fig. 7) 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 5), 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* (Fig. 9), defined as the average technological distance between the public firm and its private competitors (see Eq. (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 (Fig. 9). These results deliver two policy implications:

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

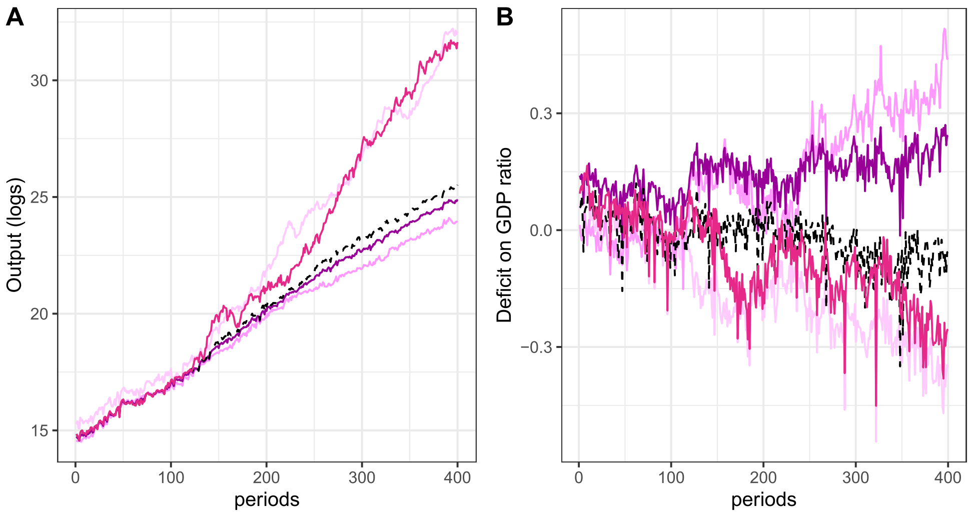

Fig. 10. Dynamics of GDP (panel A) and public deficit (panel B) in Experiment 5 (National Research Lab), multiple runs in different shades of color.

(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. Fig. 10 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. Fig. 10), resembling those displayed in Experiment 3 (i.e. unproductive spending; see panel F in Fig. 6). While experiments from I to III display a rather homogeneous behavior across runs (see the distributions of Fig. 8), 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).[24] 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 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 Fig. 11 and Table 9 in the Appendix).

The status of public finances differs sharply across experiments (see, e.g. Fig. 7). 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 Fig. 8, 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.

Crowding-in effects. 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:[25]

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

[24] 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.

[25] Our artificial economy offers a convenient setting to estimate Eq. (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.

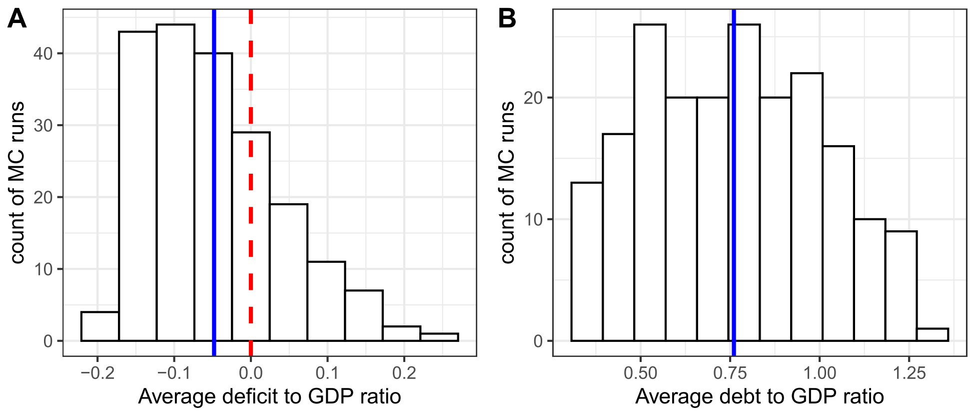

Fig. 11. Status of public finances under Experiment 5 (National Research Lab); panel A reports the distribution of simulation-average deficits and panel B the distribution of simulation-average debt; 200 runs are used. The blue line indicates the mean while the dashed red line crosses the x-axis at zero. (For interpretation of the references to colours in this figure legend, the reader is referred to the web version of this article.)

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. 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	1,960,000	1,960,000	1,960,000	1,960,000	1,960,000	1,960,000
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 7
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	1,960,000	1,960,000	1,960,000	1,960,000	1,960,000	1,960,000
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.

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 6 and 7). 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., 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 7 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 facilitate the discovery of 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, and such a result is stronger for direct innovation policies.

Overall, this paper supports the idea that public policies aimed at stimulating basic research improve the economic performance (see e.g., Akcigit et al., 2020; Kantor and Whalley, 2022) and stimulate the private search for innovations (e.g. Rosenberg and Nelson, 1994). 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; Kantor and Whalley, 2022). While mission-oriented policies are often criticized for the alleged inability of the government to select challenges and technologies, we find that innovation policies inspired by an Entrepreneurial State approach are valuable independently of the specific mission to be targeted. Though risky, they are way more effective than a number of alternatives at enlarging the pool of knowledge and the technological opportunities available to the economy as well as at facilitating their diffusion. This is beneficial and socially desirable per-se. Hence, given a societal challenge, our results hint that genuine Entrepreneurial State-like policies should patiently promote the discovery of radical innovations through broad and ambitious research-oriented programs, sustain the costs of eventual early failures, and ease knowledge diffusion through public-private interactions. Such a genuine Entrepreneurial State approach will further solve the apparent short term trade-offs between innovation policies and other forms of public spending.

This work can be extended along several directions. One natural avenue of further research would formalize mechanisms of interactions and research partnerships between private firms, public firms and the NRL, thereby linking the present analysis to the role of R&D networks. Further, 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, 2022, and references therein). Third, 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). Fourth, 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., 2019; 2021; 2018b; 2020), which builds on the shoulders of the baseline model analyzed here. Relatedly, a promising new research avenue we plan undertaking will enrich a multi-sector model (e.g. Dosi et al., 2022) with lobbying dynamics (e.g. Isley et al., 2015), enabling the analysis of various innovation policies targeting endogenously defined and possibly competing missions.

Acknowledgments

The authors are indebted with Herbert Dawid, Mattia Guerini, Pierre Mohnen, Gianluca Pallante, Emanuele Russo, Danilo Spinola, Tania Treibich and three anonymous reviewers for helpful comments and discussions. Further, the authors thank all participants to EMAEE 2017, WEHIA 2018, WEHIA 2019, EAEPE 2018, EAEPE 2019, CEF 2018 and the First European Conference "Moving the Frontier of the Macroeconomic Modelling of Research & Innovation". The authors acknowledge financial support from the H2020 project GROWINPRO (GA No 822781).

Appendix.

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). Overall, we find that results are robust to changes in the value of parameters governing the probability of discovering a radical innovation, the size of the shift in technological opportunities and the cost of public debt. This reinforces our conclusion about the dynamics of growth and the health of public finances in the scenarios where Entrepreneurial State policies are implemented. In addition, we notice that (i) when the probability of a radical innovation is more sensitive to the cumulative stock of R&D, Exp. IV sometimes triggers a radical innovation by either a private or public firm, which did not happen in the benchmark configuration; (ii), if the shift in technological opportunity due to a radical innovation is sufficiently large, the average deficit over the simulation turns to positive thanks to the super hysteric impact on growth.

Additional policy and behavioural experiments

In what follows, we perform a battery of simulation exercises wherein we (i) study indirect innovation policies under alternative designs, (ii) test all policies under different R&D investment routines, and (iii) modify the equation governing the probability of a radical innovation. Overall, our results are robust to such alternative configurations which nonetheless provide some novel insights.

Indirect innovation policies under alternative designs

Here we modify the design of indirect innovation policies (Exp. I and II). First, we consider a variant of Exp. I wherein we introduce a R&D tax credit; second, we test different values of the pay-back parameter *b*, which modifies the consumption-good firm's patience in renovating their capital stock. In particular, the first variant of Exp. I introduces a tax credit that

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; runs RI indicate the share of runs with at least one radical innovation. GDP gr., Une. and Def. stands for GDP growth unemployment and deficit to GDP ratio, respectively..

	Exp. IV					Exp. V				
	# RI	runs RI	GDP gr.	Une.	Def.	# RI	runs RI	GDP gr.	Une.	Def.
benchmark	0	0%	3.40%	5.38%	5.17%	2.15	86%	4.15%	5.37%	3.39%
η_1=1	0.02	1%	3.41%	5.30%	5.10%	3.22	92%	5.22%	3.82%	2.16%
η_1=1.2	0	0%	3.40%	5.38%	5.17%	2.46	88%	4.33%	4.45%	3.10%
η_1=2	0	0%	3.40%	5.38%	5.17%	0.21	18%	2.76%	6.83%	6.13%
η_2=4.5	0.16	14%	3.47%	4.93%	5.02%	4.31	100%	6.23%	3.67%	−2.47%
η_2=5	0.03	3%	3.41%	5.35%	5.15%	3.58	98%	5.72%	3.80%	−1.03%
η_2=7	0	0%	3.40%	5.38%	5.17%	0.65	60%	2.90%	6.24%	5.89%
ϱ=0.05	0	0%	3.40%	5.38%	8.66%	2.15	86%	4.15%	5.37%	4.71%
ϱ=0.1	0	0%	3.40%	5.38%	10.34%	2.15	86%	4.15%	5.37%	8.49%
ϱ=0.005	0	0%	3.40%	5.38%	4.51%	2.15	86%	4.15%	5.37%	3.08%
χ^{RI}= 0.0125	0	0%	3.40%	5.38%	5.17%	2.15	86%	3.61%	6.01%	4.32%
χ^{RI}= 0.05	0	0%	3.40%	5.38%	5.17%	2.15	86%	6.73%	2.93%	−2.88%

Table 10
Comparison of different experiments on alternative designs of indirect innovation policies. 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 *
Ib - R&D tax credits, no anticip.	1.03	0.95*	0.96	1.02	1.09*
Ic - R&D tax credits, anticipation	1.11*	0.90*	0.95*	1.20 *	1.18 *
II - Invest. tax disc. (b=120)	1.08	1.22 *	0.97	1.38 *	1.34 *
II - Invest. tax disc. (b=90)	1.15*	1.42 *	1.05	1.42 *	1.21 *
II - Invest. tax disc. (b=160)	1.02	1.10*	1.08*	0.93*	1.39*

capital-good firms receive in the period after having perfomed R&D (Exp. Ib); the fiscal discount amounts to a percentage d_{TD}^{RD} of its previous expenditures in R&D:

$$D_{TD,i}^{RD}(t) = d_{TD}^{RD} RD_i(t-1). \tag{26}$$

Such discount boost firms profits, but it does not immediately translate into different R&D expenditures. Hence, we further extend the experiment by assuming that capital good firms believe the policy regime, anticipate the effect of the fiscal discount and increase their R&D by an equal amount (Exp. Ic). Finally, we experiment with different values of the pay-back parameter b (see Eqs. 10 and 14), which proxies consumptio good firms' "patience" in obtaining net returns on their investments and, hence, could affect the effectiveness of tax discounts on physical investments.

The results in Table 10 highlight that discounts on physical investments (Exp. II), aimed at fostering technological diffusion, deliver different dynamics with respect to R&D tax credits. Indeed, R&D credits prove more effective that physical investment discounts at stimulating growth, yet only if we assume that firms anticipate the fiscal relief and destinate an equal amount to R&D (Exp. Ic). In this scenario, the economy-wide performance is superior to the case of subsidies (Exp. I), as lower taxation improves firms' balance-sheet and reduce the volatility of growth, cushioning downward phases of the cycle. However, we stress that the empirical literature reports mixed evidence about the crowding-in effect of R&D tax credits, as some studies suggest that firms might just use the policy opportunistically to boost their profits (Marino et al., 2016; Mohnen et al., 2017) while keeping search efforts unaltered. Indeed, Exp. Ib clearly shows that when firms do not anticipate the policy and fail to increase their R&D expenditures the public intervention turns largely ineffective. Finally, we find that the economy-wide impact of physical investments' discounts depends heavily on firms' "patience" in repaying their investments in capital goods: lower values of the pay-back parameter b boost investment and growth, though this comes at the cost of larger fluctuations.

Innovation policies under different R&D investment routines

So far we have assumed that capital-good firms' R&D spending correspond to a constant fraction of their past revenues. Though there is empirical evidence supporting our modelling choice (Coad and Rao, 2010), some heterogeneity in R&D intensity exist and might relate to firms' size and their growth dynamics (e.g. Coad and Rao, 2010; Cohen and Klepper, 1992). In particular, Coad and Rao (2010) further robustly show that manufacturing firms are relative less willing to decrease

Table 11
Comparison of innnovation policies under various specifications of R&D investment routines. Rows reports the average relative performance of each experiment with respect to the "no innovation policy" baseline (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. Symmetric reaction to growth corresponds to $\theta_1 = \theta_2 = -0.5$ and $\theta_3 = 0$; asymmetric reaction to growth corresponds to $\theta_1 = -0.7$, $\theta_2 = -0.3$ and $\theta_3 = 0$; dependence on size corresponds to $\theta_1 = \theta_2 = 0$ and $\theta_3 = 0.1$.

	symmetric reaction to growth			*asymmetric reaction to growth*		
	GDP growth	Growth vol.	Deficit	GDP growth	Growth vol.	Deficit
Baseline	2.55%	0.10	4.11%	2.67%	0.13	2.17%
Exp. I	1.13*	0.92*	1.13*	1.18*	0.87*	1.05
Exp. II	1.08	1.20*	1.32*	1.08	1.24*	1.33*
Exp. IV	1.33*	1.47*	1.17*	1.35*	1.5*	1.14*
Exp. V	1.49*	1.87*	0.85*	1.52*	1.83*	0.81*

	dependence on size		
	GDP growth	**Growth vol.**	**Deficit**
Baseline	2.75%	0.09	4.02%
Exp. I	1.12*	0.98	1.12*
Exp. II	1.09	1.18*	1.35*
Exp. IV	1.45*	1.67*	1.07*
Exp. V	1.50*	1.84*	0.90*

R&D after a negative growth episode than they are in increasing it after a positive growth shock. Moreover, Cohen and Klepper (1992) argue that - within industries - R&D intensity proportionally depends on the relative size of the search intensity effort. In line with this empirical evidence, we compare our innovation policies under different rules determining R&D spending, wherein we include dependence of the search intensity on experienced growth shocks and heterogenous R&D intensity:

$$RD_i(t) = \upsilon S_i(t-1) * [1 + \theta_1 g_i^S(t-1)1[g_i^S < 0] + \theta_2 g_i^S(t-1)1[g_i^S > 0] + \theta_3 f_{RD,i}(t-1)] \tag{27}$$

where $\theta_1 < 0$, $\theta_2 < 0$, $\theta_3 > 0$, g^S indicates sales growth, f_{RD} the R&D expenditure relative to the overall R&D effort of capital-good firms and $1[\cdot]$ is and indicator function.

Table 11 collects the results. We find that when R&D expenditures adjusts to growth shocks, either symmetrically or asymmetrically, R&D subsidies become comparatively more appealing than in the benchmark case where R&D solely depends on past revenues. Indeed, they counterbalance the dependence of R&D spending from sales fluctuations at the firm level. Intuitively, when R&D reacts asymmetrically to past sales growth (and more pronouncedly to negative growth shocks), subsidies reinforce the countercyclical effect of R&D that characterizes this scenario. Differently, the impact of all other experiments is similar to the analysis reported in the main text. Further, when we allow R&D investment to depend on its size, our results are broadly confirmed. The only notable difference concerns Experiment 4 (Public firm). Indeed, under this scenario, the larger tendency to spend in R&D of the public firm (see Eq. 23) vis-á-vis other capital-good firms kickstarts a virtuous cycle triggering higher search for new technologies and lower risk of lagging behind in the technological space. This reinforces the diffusion process that lies at the core of the growth stimulus brought about by a public firm. Indeed, in the set-up where R&D adjusts to size, Experiment 4 and Experiment 5 turned out being almost comparable with respect to their economy-wide effects.

Alternative assumptions on radical innovation occurrence

We test the robustness of our results to an alternative assumption concerning the occurrence of a radical innovation. Specifically, we design a scenario - labeled as Exp. V (only own R&D) - where the probability of discovering a radical innovation (see Eqs. 12 and 24) depends only on the cumulative R&D performed within the organization. This holds true both for the NRL and other capital good firms.

Table 12 collects the results and contrast them with the baseline and the Exp. V discussed the main text (standard). In the baseline scenario, we find no differences between the current setup of the model with respect to the benchmark one (see Table 4). Indeed, in both cases, the cumulative stock of knowledge developed within a single capital good firm turned out being insufficient to the discovery of a radical innovation during our simulation runs (see also Table 9). Similarly, the NRL is way less effective at stimulating growth than in the benchmark Exp. V, wherein it leverages on the knowledge stock of the entire economy. It achieves - on average - less radical innovations, which obviously reflects on the average dynamics of the model. Indeed, the economy shows significantly lower growth, relatively deficits, as well as markedly reduced volatility than in the standard experiment. Unemployment is low in both scenarios and statistically significant difference are not found. On average, this setting of experiment V is still superior to other innovation policies (Table 4).

Table 12
Baseline and two alternative specifications of Experiment 5: as in the main text (standard) and with radical innovation depending on own cumulative R&D. The second and third rows report the average relative performance of with respect to the "no innovation policy" baseline (Baseline) over 200 Monte Carlo runs, but for the number of radical innovations (# rad. inn). Symbol * indicates a statistically significant difference with respect to the baseline, at 5% and resulting from a *t*-test on the means. Similarly, symbol † indicates a significant difference with respect to the Exp. V of the main text (standard). GDP vol. stands for GDP volatility proxied by the standard deviation of the growth process; unempl. stands for unemployment; deficit is expressed as relative to GDP.

Policy	# rad. inn.	GDP growth	GDP vol.	Unempl.	Deficit
Baseline	0	2.68%	0.08	6.10%	4.34%
Exp V (standard)	2.15	1.55*	2.01*	0.88*	0.78*
Exp. V (only own R&D)	0.96	1.23*,†	1.47*,†	0.92*	0.89*,†

References

Aghion, P., Howitt, P., 1992. A model of growth through creative destruction. Econometrica 60 (2), 323–351. http://www.jstor.org/stable/2951599.
Aistleitner, M., Gräbner, C., Hornykewycz, A., 2021. Theory and empirics of capability accumulation: implications for macroeconomic modeling. Res Policy 50 (6), 104258.
Akcigit, U., Hanley, D., Serrano-Velarde, N., 2020. Back to basics: basic research spillovers, innovation policy and growth. Rev Econ Stud 88 (1), 1–43. doi:10.1093/restud/rdaa061.
Andriani, P., Cattani, G., 2016. Exaptation as source of creativity, innovation, and diversity: introduction to the special section. Industrial and Corporate Change 25 (1), 115–131.
Arrow, K.J., 1951. An extension of the basic theorems of classical welfare economics. Technical Report. Proceedings of the second berkeley symposium on mathematical statistics and probability.
Arrow, K.J., 1962. Economic welfare and the allocation of resources for invention. In: Nelson, R.R. (Ed.), The Rate and Direction of Inventive Activity. Princeton University Press, pp. 609–625.
Arrow, K.J., 1996. Technical information and industrial structure. Industrial and corporate change 5 (2), 645–652.
Ausloos, M., Miśkiewicz, J., Sanglier, M., 2004. The durations of recession and prosperity: does their distribution follow a power or an exponential law? Physica A 339 (3–4), 548–558. doi:10.1016/j.physa.2004.03.005.
Bartelsman, E., Scarpetta, S., Schivardi, F., 2005. Comparative analysis of firm demographics and survival: evidence from micro-level sources in OECD countries. Industrial and Corporate Change 14 (3), 365–391.
Bartelsman, E.J., Doms, M., 2000. Understanding productivity: lessons from longitudinal microdata. J Econ Lit 38 (3), 569–594.
Becker, B., 2015. Public r&d policies and private r&d investment: asurvey of the empirical evidence. J Econ Surv 29 (5), 917–942.
Block, F.L., Keller, M.R., 2015. State of Innovation: The US Government's Role in Technology Development. Routledge.
Bloom, N., Van Reenen, J., Williams, H., 2019. A toolkit of policies to promote innovation. Journal of Economic Perspectives 33 (3), 163–184.
Boca, A., Galeotti, M., Himmelberg, C.P., Rota, P., 2008. Investment and time to plan and build: a comparison of structures vs. equipment in a panel of Italian firms. J Eur Econ Assoc 6 (4), 864–889.
Borrás, S., Edquist, C., 2013. The choice of innovation policy instruments. Technol Forecast Soc Change 80 (8), 1513–1522.
Bottazzi, G., Secchi, A., 2003. Common properties and sectoral specificities in the dynamics of US manufacturing companies. Review of Industrial Organization 23 (3–4), 217–232.
Bottazzi, G., Secchi, A., 2006. Explaining the distribution of firm growth rates. Rand J Econ 37 (2), 235–256.
Burns, A.F., Mitchell, W.C., 1946. Measuring business cycles. National Bureau of Economic Research. http://EconPapers.repec.org/RePEc:nbr:nberbk:burn46-1.
Bush, V., et al., 1945. Science, the endless frontier. Technical Report. US Office of Scientific Research and Development.
Caiani, A., Russo, A., Gallegati, M., 2019. Does inequality hamper innovation and growth? an AB-SFC analysis. Journal of Evolutionary Economics 29 (1), 177–228.
Castaldi, C., Dosi, G., 2009. The patterns of output growth of firms and countries: scale invariances and scale specificities. Empir Econ 37 (3), 475–495. http://EconPapers.repec.org/RePEc:spr:empeco:v:37:y:2009:i:3:p:475-495.
Castelnovo, P., Florio, M., 2020. Mission-oriented public organizations for knowledge creation. In: The Routledge Handbook of State-Owned Enterprises. Routledge, pp. 587–604.
Cerra, V., Fatás, A., Saxena, S., 2021. Hysteresis and business cycles forthcoming.
Chataway, J., Brusoni, S., Cacciatori, E., Hanlin, R., Orsenigo, L., 2007. The international AIDS vaccine initiative (IAVI) in a changing landscape of vaccine development: a public/private partnership as knowledge broker and integrator. The European Journal of Development Research 19 (1), 100–117.
Chiang, J.-T., 1991. From 'mission-oriented'to 'diffusion-oriented'paradigm: the new trend of US industrial technology policy. Technovation 11 (6), 339–356.
Cimoli, M., Dosi, G., Maskus, K.E., Okediji, R.L., Reichman, J.H., Stiglitz, J.E., 2014. Intellectual Property Rights: Legal and Economic Challenges for Development. Oxford University Press.
Cimoli, M., Dosi, G., Stiglitz, J., 2009. Industrial Policy and Development: The Political Economy of Capabilities Accumulation. Oxford University Press.
Coad, A., Rao, R., 2010. Firm growth and R&D expenditure. Economics of Innovation and New Technology 19 (2), 127–145.
Cohen, W.M., 2010. Fifty years of empirical studies of innovative activity and performance. In: Handbook of the Economics of Innovation, Vol. 1. Elsevier, pp. 129–213.
Cohen, W.M., Klepper, S., 1992. The anatomy of industry R&D intensity distributions. Am Econ Rev 773–799.
Cohen, W.M., Levin, R.C., Mowery, D.C., 1987. Firm size and r & d intensity: a re-examination. J Ind Econ 543–565.
Criscuolo, C., Gonne, N., Kitazawa, K., Lalanne, G., 2020. A fresh look at industrial policies: old debates, new perspectives. Technical Report. OECD, DSTI-CIIE.
Dawid, H., 2006. Agent-based models of innovation and technological change. Handbook of computational economics 2, 1235–1272.
Dawid, H., Delli Gatti, D., 2018. Agent-based macroeconomics. Handbook of Computational Economics 4, 63–156.
Dawid, H., Gemkow, S., Harting, P., Kabus, K., Neugart, M., Wersching, K., 2008. Skills, innovation, and growth: an agent-based policy analysis. Jahrbücher für Nationalökonomie und Statistik 228 (2–3), 251–275.
DeLong, D.W., Storey, J., et al., 2004. Lost Knowledge: Confronting the Threat of an Aging Workforce. Oxford University Press.
Di Comite, F., Kancs, d., 2015. Macro-economic models for R&D and innovation policies. Technical Report. IPTS Working Papers on Corporate R&D and Innovation.
Dimos, C., Pugh, G., 2016. The effectiveness of R&D subsidies: ameta-regression analysis of the evaluation literature. Res Policy 45 (4), 797–815.
Doms, M., Dunne, T., 1998. Capital adjustment patterns in manufacturing plants. Rev Econ Dyn 1 (2), 409–429.
Dosi, G., 1982. Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. Res Policy 11 (3), 147–162.

Dosi, G., 1988. Sources, procedures, and microeconomic effects of innovation. J Econ Lit 26 (3), 1120–1171. http://www.jstor.org/stable/2726526.
Dosi, G., 2007. Statistical regularities in the evolution of industries. a guide through some evidence and challenges for the theory. In: Malerba, F., Brusoni, S. (Eds.), Perspectives on innovation. Cambridge University Press, pp. 1110–1121.
Dosi, G., Fagiolo, G., Napoletano, M., Roventini, A., 2013. Income distribution, credit and fiscal policies in an agent-based Keynesian model. Journal of Economic Dynamics and Control 37 (8), 1598–1625. doi:10.1016/j.jedc.2012.11.008.
Dosi, G., Fagiolo, G., Napoletano, M., Roventini, A., Treibich, T., 2015. Fiscal and monetary policies in complex evolving economies. Journal of Economic Dynamics and Control 52, 166–189. doi:10.1016/j.jedc.2014.11.014.
Dosi, G., Fagiolo, G., Roventini, A., 2010. Schumpeter meeting Keynes: a policy-friendly model of endogenous growth and business cycles. Journal of Economic Dynamics and Control 34 (9), 1748–1767.
Dosi, G., Freeman, C., Fabiani, S., 1994. The process of economic development: introducing some stylized facts and theories on technologies, firms and institutions. Industrial and corporate change 3 (1), 1–45.
Dosi, G., Freeman, R.B., Pereira, M.C., Roventini, A., Virgillito, M.E., 2020. The impact of deunionization on the growth and dispersion of productivity and pay. Technical Report. National Bureau of Economic Research.
Dosi, G., Marengo, L., Pasquali, C., 2006. How much should society fuel the greed of innovators?: on the relations between appropriability, opportunities and rates of innovation. Res Policy 35 (8), 1110–1121.
Dosi, G., Napoletano, M., Roventini, A., Stiglitz, J.E., Treibich, T., 2020. Rational heuristics? expectations and behaviors in evolving economies with heterogeneous interacting agents. Econ Inq 58 (3), 1487–1516.
Dosi, G., Napoletano, M., Roventini, A., Treibich, T., 2016. The short- and long-run damages of fiscal austerity: Keynes beyond schumpeter. In: Stiglitz, J., Guzman, M. (Eds.), Contemporary Issues in Macroeconomics. Palgrave Macmillan UK.
Dosi, G., Napoletano, M., Roventini, A., Treibich, T., 2017. Micro and macro policies in the keynes+ schumpeter evolutionary models. Journal of Evolutionary Economics 27 (1), 63–90.
Dosi, G., Nelson, R.R., 2010. Technological change and industrial dynamics as evolutionary processes. In: Hall, B.H., Rosenberg, N. (Eds.), Handbook of the Economics of Innovation. Elsevier: Amsterdam, pp. 51–127. chapter 4
Dosi, G., Pereira, M.C., Roventini, A., Virgillito, M.E., 2017. When more flexibility yields more fragility: the microfoundations of Keynesian aggregate unemployment. Journal of Economic Dynamics and Control 81, 162–186.
Dosi, G., Pereira, M.C., Roventini, A., Virgillito, M.E., 2018. Causes and consequences of hysteresis: aggregate demand, productivity, and employment. Industrial and Corporate Change 27 (6), 1015–1044.
Dosi, G., Pereira, M.C., Roventini, A., Virgillito, M.E., 2022. Technological paradigms, labour creation and destruction in a multi-sector agent-based model. Research Policy 51 (10), 104565.
Dosi, G., Roventini, A., 2019. More is different... and complex!: the case for agent-based macroeconomics. Journal of Evolutionary Economics 29, 1–37. doi:10.1007/s00191-019-00609-y.
Dosi, G., Roventini, A., Russo, E., 2019. Endogenous growth and global divergence in a multi-country agent-based model. Journal of Economic Dynamics and Control 101, 101–129.
Dosi, G., Roventini, A., Russo, E., et al., 2020. Public policies and the art of catching up: matching the historical evidence with a multicountry agent-based model. Industrial and Corporate Change doi:10.1093/icc/dtaa057.
Dosi, G., Stiglitz, J.E., 2014. The role of intellectual property rights in the development process, with some lessons from developed countries: an introduction. In: Cimoli, M., Dosi, G., Stiglitz, J.E. (Eds.), Intellectual Property Rights: Legal and Economic Challenges for Development. Oxford University Press Oxford.
Dosi, G., Virgillito, M.E., 2017. In order to stand up you must keep cycling: change and coordination in complex evolving economies. Structural Change and Economic Dynamics 56, 353–364.
Dunlap-Hinkler, D., Kotabe, M., Mudambi, R., 2010. A story of breakthrough versus incremental innovation: corporate entrepreneurship in the global pharmaceutical industry. Strategic Entrepreneurship Journal 4 (2), 106–127.
Edler, J., Fagerberg, J., 2017. Innovation policy: what, why, and how. Oxford Review of Economic Policy 33 (1), 2–23.
Edquist, C., 2011. Design of innovation policy through diagnostic analysis: identification of systemic problems (or failures). Industrial and corporate change 20 (6), 1725–1753.
Eisner, R., 1972. Components of capital expenditures: replacement and modernization versus expansion. Rev Econ Stat 54 (3), 297–305.
Engel, D., Rothgang, M., Eckl, V., 2016. Systemic aspects of r&d policy subsidies for r&d collaborations and their effects on private r&d. Industry and Innovation 23 (2), 206–222.
Ergas, H., 1987. Does technology policy matter? In: Guile, B.R., Brooks, H. (Eds.), Technology and Global Industry: Companies and Nations in the World Economy. National Academy Press Washington, DC.
EU, 2020. Moving the frontier of macroeconomic modelling of research and innovation policy. Technical Report. Directorate General for Research and Innovation (European Commission) doi:10.2777/34199s.
Fagerberg, J., 2017. Innovation policy: rationales, lessons and challenges. J Econ Surv 31 (2), 497–512.
Fagiolo, G., Giachini, D., Roventini, A., 2020. Innovation, finance, and economic growth: an agent-based approach. Journal of Economic Interaction and Coordination 15 (3), 703–736.
Fagiolo, G., Guerini, M., Lamperti, F., Moneta, A., Roventini, A., 2019. Validation of agent-based models in economics and finance. In: Computer Simulation Validation. Springer, pp. 763–787.
Fagiolo, G., Napoletano, M., Roventini, A., 2008. Are output growth-rate distributions fat-tailed? some evidence from OECD countries. Journal of Applied Econometrics 23 (5), 639–669.
Fagiolo, G., Roventini, A., 2017. Macroeconomic policy in DSGE and agent-based models redux: new developments and challenges ahead. Journal of Artificial Societies and Social Simulation 20 (1).
Feldstein, M.S., Foot, D.K., 1971. The other half of gross investment: replacement and modernization expenditures. The Review of Economics Statistic 53 (1), 49–58.
Foray, D., Mowery, D.C., Nelson, R.R., 2012. Public r&d and social challenges: what lessons from mission r&d programs? Res Policy 41 (10), 1697–1702.
Freeman, C., 1987. Technology, Policy, and Economic Performance: Lessons from Japan. Pinter Pub Ltd.
Freeman, C., Soete, L., 1997. The Economics of Industrial Innovation. Psychology Press.
Goolsbee, A., 1998. The business cycle, financial performance, and the retirement of capital goods. Rev Econ Dyn 1 (2), 474–496.
Gräbner, C., Hornykewycz, A., 2022. Capability accumulation and product innovation: an agent-based perspective. Journal of Evolutionary Economics 32 (1), 87–121.
Grilli, L., Mazzucato, M., Meoli, M., Scellato, G., 2018. Sowing the seeds of the future: policies for financing tomorrow's innovations. Technol Forecast Soc Change 127, 1–7.
Gross, D.P., Sampat, B.N., 2020. Inventing the endless frontier: The effects of the World War II research effort on post-war innovation. Technical Report. National Bureau of Economic Research.
Gross, D.P., Sampat, B.N., 2021. The Economics of Crisis Innovation Policy: A Historical Perspective. Technical Report. National Bureau of Economic Research.
Guellec, D., Van Pottelsberghe De La Potterie, B., 2003. The impact of public R&D expenditure on business R&D. Economics of innovation and new technology 12 (3), 225–243.
Guerini, M., Moneta, A., 2017. A method for agent-based models validation. Journal of Economic Dynamics and Control 82, 125–141.
Haldane, A.G., Turrell, A.E., 2019. Drawing on different disciplines: macroeconomic agent-based models. Journal of Evolutionary Economics 29, 39–66. doi:10.1007/s00191-018-0557-5.
Hidalgo, C.A., Klinger, B., Barabási, A.-L., Hausmann, R., 2007. The product space conditions the development of nations. Science 317 (5837), 482–487.

Isley, S.C., Lempert, R.J., Popper, S.W., Vardavas, R., 2015. The effect of near-term policy choices on long-term greenhouse gas transformation pathways. Global Environ. Change 34, 147–158.
Jaimovich, N., Floetotto, M., 2008. Firm dynamics, markup variations, and the business cycle. J Monet Econ 55 (7), 1238–1252.
Kantor, S., Whalley, A., 2022. Moonshot: Public R&D and growth.
Kaplan, S., Vakili, K., 2015. The double-edged sword of recombination in breakthrough innovation. Strategic Management Journal 36 (10), 1435–1457.
Kuznets, S.S., Murphy, J.T., 1966. Modern Economic Growth: Rate, Structure, and Spread, Vol. 2. Yale University Press New Haven.
Lamperti, F., 2018. Empirical validation of simulated models through the GSL-div: an illustrative application. Journal of Economic Interaction and Coordination 13 (1), 143–171.
Lamperti, F., 2018. An information theoretic criterion for empirical validation of simulation models. Econometrics and Statistics 5, 83–106.
Lamperti, F., Bosetti, V., Roventini, A., Tavoni, M., 2019. The public costs of climate-induced financial instability. Nat Clim Chang 9 (11), 829–833.
Lamperti, F., Bosetti, V., Roventini, A., Tavoni, M., Treibich, T., 2021. Three green financial policies to address climate risks. Journal of Financial Stability 54, 100875. doi:10.1016/j.jfs.2021.100875.
Lamperti, F., Dosi, G., Napoletano, M., Roventini, A., Sapio, A., 2018. Faraway, so close: coupled climate and economic dynamics in an agent-based integrated assessment model. Ecol. Econ. 150, 315–339.
Lamperti, F., Dosi, G., Napoletano, M., Roventini, A., Sapio, A., 2018. Faraway, so close: coupled climate and economic dynamics in an agent-based integrated assessment model. Ecol. Econ. 150, 315–339. doi:10.1016/j.ecolecon.2018.03.023.
Lamperti, F., Dosi, G., Napoletano, M., Roventini, A., Sapio, A., 2020. Climate change and green transitions in an agent-based integrated assessment model. Technol Forecast Soc Change 153, 119806.
Lamperti, F., Mattei, C.E., 2018. Going up and down: rethinking the empirics of growth in the developing and newly industrialized world. Journal of Evolutionary Economics 28 (4), 749–784.
Lamperti, F., Roventini, A., Sani, A., 2018. Agent-based model calibration using machine learning surrogates. Journal of Economic Dynamics and Control 90, 366–389.
Lazonick, W., Tulum, O., 2011. Us biopharmaceutical finance and the sustainability of the biotech business model. Res Policy 40 (9), 1170–1187.
Levin, R.C., Klevorick, A.K., Nelson, R.R., Winter, S.G., Gilbert, R., Griliches, Z., 1987. Appropriating the returns from industrial research and development. Brookings Pap Econ Act 1987 (3), 783–831.
Lorentz, A., Ciarli, T., Savona, M., Valente, M., 2016. The effect of demand-driven structural transformations on growth and technological change. Journal of Evolutionary Economics 26 (1), 219–246.
Lundvall, B.-A., 1988. Innovation as an interactive process: from user-producer interaction to the national system of innovation. In: Dosi, G. (Ed.), Technical Change and Economic Theory. London: Pinter, pp. 349–369.
Lundvall, B.-A., 2010. National systems of innovation: Toward a theory of innovation and interactive learning. London: Pinter.
Malerba, F., 2002. Sectoral systems of innovation and production. Res Policy 31 (2), 247–264.
Marino, M., Lhuillery, S., Parrotta, P., Sala, D., 2016. Additionality or crowding-out? an overall evaluation of public r&d subsidy on private r&d expenditure. Res Policy 45 (9), 1715–1730.
Mazzucato, M., 2013. The Entrepreneurial State: Debunking Public vs. Private Sector Myths. Anthem Press, London.
Mazzucato, M., 2015. The green entrepreneurial state. In: Scoones, I., Leach, M., Newell, P. (Eds.), The Politics of Green Transformations; Scoones, I., Leach, M., Newell, P., Eds. Routledge London, pp. 134–152.
Mazzucato, M., 2016. From market fixing to market-creating: a new framework for innovation policy. Industry and Innovation 23 (2), 140–156.
Mazzucato, M., 2018. Mission-oriented innovation policies: challenges and opportunities. Industrial and Corporate Change 27 (5), 803–815.
Mazzucato, M., 2018. Mission-oriented research & innovation in the European Union. Technical Report. Directorate-General for Research and Innovation (European Commission).
Mazzucato, M., 2019. Governing missions in the European Union. Technical Report. Directorate-General for Research and Innovation (European Commission).
Mazzucato, M., 2021. Mission Economy. Penguin, Allen Lane-Penguin.
Mazzucato, M., Semieniuk, G., 2017. Public financing of innovation: new questions. Oxford Review of Economic Policy 33 (1), 24–48.
Mazzucato, M., Semieniuk, G., 2018. Financing renewable energy: who is financing what and why it matters. Technol Forecast Soc Change 127, 8–22.
Metcalfe, J.S., 1994. Evolutionary economics and technology policy. The economic journal 104 (425), 931–944.
Metcalfe, J.S., 1995. Technology systems and technology policy in an evolutionary framework. Cambridge J Econ 19 (1), 25–46.
Metcalfe, J.S., 2005. Systems failure and the case for innovation policy. In: Innovation Policy in a Knowledge-based Economy. Springer, pp. 47–74.
Mohnen, P., Vankan, A., Verspagen, B., 2017. Evaluating the innovation box tax policy instrument in the netherlands, 2007–13. Oxford Review of Economic Policy 33 (1), 141–156.
Moretti, E., Steinwender, C., Van Reenen, J., 2019. The Intellectual Spoils of War? Defense R&D, Productivity and International Spillovers. Technical Report. National Bureau of Economic Research.
Motoyama, Y., Appelbaum, R., Parker, R., 2011. The national nanotechnology initiative: federal support for science and technology, or hidden industrial policy? Technol Soc 33 (1–2), 109–118.
Mowery, D.C., 2010. Military R&D and Innovation. In: Handbook of the Economics of Innovation, Vol. 2. Elsevier, pp. 1219–1256.
Napoletano, M., Roventini, A., Sapio, S., 2006. Are business cycles all alike? a bandpass filter analysis of Italian and US cycles. Rivista Italiana degli Economisti 1, 87–118.
Nelson, R. (Ed.), 1982. Government and Technical Progress: A Cross-industry Analysis. Pergamon Press, New York; Toronto.
Nelson, R., Winter, S., 1982. An evolutionary theory of economic change. Harvard Business School Press, Cambridge.
Nelson, R.R., 1962. Introduction. In: Nelson, R.R. (Ed.), The Rate and Direction of Inventive Activity. Princetion University Press, pp. 609–625.
Nelson, R.R., 1982. The role of knowledge in R&D efficiency. Q J Econ 97 (3), 453–470.
OECD, 2010. The OECD innovation strategy: Getting a head start on tomorrow.
Pallante, G., Russo, E., Roventini, A., et al., 2020. Does mission-oriented funding stimulate private R&D? Evidence from military R&D for US states. Technical Report 2020/32. LEM Working Papers, Sant'Anna School of Advanced Studies.
Papageorgiadis, N., Sharma, A., 2016. Intellectual property rights and innovation: a panel analysis. Econ Lett 141, 70–72.
Phelps, E.S., Winter, S.G., 1970. Optimal price policy under atomistic competition. In: Microeconomic Foundations of Employment and Inflation Theory. WW Norton New York, pp. 309–337.
Phene, A., Fladmoe-Lindquist, K., Marsh, L., 2006. Breakthrough innovations in the US biotechnology industry: the effects of technological space and geographic origin. Strategic management journal 27 (4), 369–388.
Polanyi, K., 1944. The Great Transformation: The Political and Economic Origins of Our Time. Boston: Beacon.
Reissl, S., Caiani, A., Lamperti, F., Guerini, M., Vanni, F., Fagiolo, G., Ferraresi, T., Ghezzi, L., Napoletano, M., Roventini, A., et al., 2021. Assessing the economic effects of lockdowns in Italy: a dynamic Input-Output approach. Technical Report 2021/03. LEM Working Papers, Sant'Anna School of Advanced Studies.
Romer, P.M., 1986. Increasing returns and long-run growth. Journal of political economy 94 (5), 1002–1037.
Rosenberg, N., Nelson, R.R., 1994. American universities and technical advance in industry. Res Policy 23 (3), 323–348.
Rotemberg, J.J., 2008. Behavioral aspects of price setting, and their policy implications. Technical Report. National Bureau of Economic Research.
Russo, A., Catalano, M., Gaffeo, E., Gallegati, M., Napoletano, M., 2007. Industrial dynamics, fiscal policy and r&d: evidence from a computational experiment. Journal of Economic Behavior & Organization 64 (3–4), 426–447.
Ruttan, V.W., 2006. Is War Necessary for Economic Growth?: Military Procurement and Technology Development. Oxford University Press.
Santoleri, P., Mina, A., Minin, A.D., Martelli, I., 2020. The causal effects of R&D grants: evidence from a regression discontinuity. Technical Report. LEM Working Papers, Sant'Anna School of Advanced Studies.

Silverberg, G., Verspagen, B., 1994. Learning, innovation and economic growth: a long-run model of industrial dynamics. Industrial and Corporate Change 3 (1), 199–223.
Solow, R.M., 1957. Technical change and the aggregate production function. Rev Econ Stat 39 (3), 312–320.
Steffen, B., Egli, F., Schmidt, T.S., et al., 2020. The role of public banks in catalyzing private renewable energy finance. In: Donovan, C.W. (Ed.), Renewable Energy Finance: Funding The Future Of Energy. World Scientific, pp. 197–216.
Stiglitz, J.E., 1996. Whither socialism?. MIT press.
Stiglitz, J.E., 2014. Intellectual property rights, the pool of knowledge, and innovation. Technical Report. National Bureau of Economic Research.
Stock, J.H., Watson, M.W., 1999. Business cycle fluctuations in US macroeconomic time series. In: Handbook of Macroeconomics, Vol. 1, Part A. Elsevier, pp. 3–64. doi:10.1016/S1574-0048(99)01004-6.
Tacchella, A., Cristelli, M., Caldarelli, G., Gabrielli, A., Pietronero, L., 2012. A new metrics for countries' fitness and products' complexity. Sci Rep 2 (1), 1–7.
Teece, D.J., 2019. Roundtable discussion nathan rosenberg memorial issue. Industrial and Corporate Change 28 (2), 409–417.
Wälde, K., Woitek, U., 2004. R&D expenditure in G7 countries and the implications for endogenous fluctuations and growth. Econ Lett 82 (1), 91–97.
Windrum, P., Fagiolo, G., Moneta, A., 2007. Empirical validation of agent-based models: alternatives and prospects. Journal of Artificial Societies and Social Simulation 10 (2), 8.
Winter, S., 1998. Knowledge and competence as strategic assets. In: Klein, D.A. (Ed.), The Strategic Management of Intellectual Capital. Butterworth-Heinemann.
Wright, I., 2005. The duration of recessions follows an exponential not a power law. Physica A 345 (3), 608–610.
Zarnowitz, V., 1985. Recent work on business cycles in historical perspective: a review of theories and evidence. J Econ Lit 23 (2), 523–580. http://www.jstor.org/stable/2725624.
Zúñiga Vicente, J.A., Alonso-Borrego, C., Forcadell, F.J., Galán, J.I., 2014. Assessing the effect of public subsidies on firm R&D investment: a survey. J Econ Surv 28 (1), 36–67.