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REGULAR ARTICLE

Innovation, finance, and economic growth: an agent-based approach

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Abstract
This paper extends the endogenous growth agent-based model in Fagiolo and Dosi (Struct Change Econ Dyn 14(3):237–273, 2003) to study the finance–growth nexus. We explore industries where firms produce a homogeneous good using existing technologies, perform R&D activities to introduce new techniques, and imitate the most productive practices. Unlike the original model, we assume that both exploration and imitation require resources provided by banks, which pool agent savings and finance new projects via loans. We find that banking activity has a positive impact on growth. However, excessive financialization can hamper growth. Indeed, we find a significant and robust inverted U-shaped relation between financial depth and growth. Overall, our results stress the fundamental (and still poorly understood) role played by innovation in the finance–growth nexus.

Keywords Agent-based models · Innovation · Exploration versus exploitation · Endogenous growth · Banking sector · Finance–growth nexus

JEL Classification C63 · G21 · O30 · O31

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1 Introduction

In this paper, we develop an agent-based model to study the coevolution of innovation, finance, and growth. More specifically, we investigate whether credit can stimulate growth and if excessive levels of financialization can hamper the virtuous cycle between technological innovation and output growth.

In the last decades, financial activities have been playing a constantly increasing role in the operation of domestic economies across the world. Such a tendency, nowadays known as *financialization* (Epstein 2005), is evident in the share of finance-to-GDP series, which typically show an increasing trend in many developed countries (Philippon and Reshef 2013).

The issue whether such a stronger financialization impacts on the patterns of country growth is, however, still poorly understood. Historically, the first seminal studies by Bagehot (1873) and Schumpeter (1911) argued that more finance implies stronger growth. Yet, subsequent studies dismissed this conclusion, proposing instead that financial development simply follows economic growth (Robinson 1952). More recently, the empirical literature suggests that a complex and nonlinear relationship exists between finance and growth. In particular, excessive level of financialization could hamper economic growth (more on this in Sect. 2).

From a theoretical perspective, the links between financial development and economic growth might be due to market imperfection and information asymmetries (Levine 2005). Indeed, financial institutions may be beneficial for economic growth as they can reduce frictions and provide information about investment opportunities (Boyd and Prescott 1986; Acemoglu and Zilibotti 1997; Greenwood and Smith 1997).

Much of the existing models, however, do not explicitly address the role of innovation in the finance–growth nexus. Conversely, a large stream of literature grounded in the evolutionary economics tradition (Nelson and Winter 1982, 2002; Dosi and Nelson 1994, 2010) emphasizes the fundamental functions assumed by innovation in fueling self-sustaining processes of growth (Silverberg and Verspagen 1995; Fagiolo and Dosi 2003; Dosi et al. 2010, 2013, 2015). For example, evolutionary endogenous growth models stress how innovation (i.e., exploration of new technologies) is typically carried out by boundedly rational individuals through a trial-and-error process characterized by strong uncertainty (Dosi 1988). In such a setup, financial intermediation can play a fundamental role in promoting or hampering growth, depending on how it interacts with the evolutionary processes generating innovation.

In line with the foregoing intuitions, this paper explores the effects of banking activity in economies characterized by boundedly rational agents who strive to innovate in strongly uncertain environments. More specifically, we analyze whether the presence of a banking sector exerts a positive impact on growth. Furthermore, we study if, and how, an increasing financialization of the economy affects the growth patterns of the economy. To do that, we build upon the endogenous growth agent-based model introduced in Fagiolo and Dosi (2003) (FDM, thereafter).[1] The model is populated by boundedly rational agents (firms) who produce a homogeneous good using tech-

[1] For an introduction to agent-based computational economics, see Tesfatsion and Judd (2006) and LeBaron and Tesfatsion (2008). Fagiolo and Roventini (2017); Dawid and Delli Gatti (2018); Dosi and Roventini (2019) survey agent-based models in macroeconomics with emphasis on economic policy.

nologies spatially located on some productivity space. In the original model, firms can either produce, or perform R&D (and possibly generate innovations), or imitate existing techniques. However, all these activities do not require explicit resources. In particular, the only cost associated with both R&D and imitation is in terms of foregone production.

We extend the original model introducing a banking sector. We assume that, in every period, agents consume a fraction of their production and save the rest to support future imitative or innovative activities, in order to adopt new technologies and increase their future output. Imitation and exploration are now costly activities that require external resources if firms do not have sufficient internal funding. Therefore, we introduce in the model a stylized banking sector that collects agent savings as deposits and provides loans to firms willing to engage in innovation or imitation, but with insufficient internal funds. In this sense, we are considering a "best-case scenario" for banking activity and R&D results naturally correlated with credit levels. This, however, is in line with the findings of Amore et al. (2013), Cingano et al. (2016), and Giebel and Kraft (2018): an increase (a decrease) in credit supply generates higher (lower) investments and, eventually, positively (negatively) affects the innovation activity carried out by firms.

We run an extensive set of Monte Carlo experiments to study the simulated behavior of our economy. Our results show that, in general, the introduction of a banking sector allows for higher growth (and lower output volatility) in the long run. We then study the effects of increasing the degree of financialization in the economy. In order to measure financialization, we focus on financial depth, defined as total amount of loans over GDP (Beck and Levine 2004). We find that the relation between financial depth and growth is nonlinear and bell shaped. This implies that, for low financialization levels, increasing financialization has a positive marginal effect on growth, while the sign is reversed for larger financial depth values.

The intuition behind our results is straightforward. If banks are present in the economy, the financial constraints of firms are relaxed. They can therefore perform more R&D and ultimately introduce at a higher pace innovative technologies that quickly diffuse in the economy. This has a positive impact on the average growth rate of the economy. However, if banks excessively finance R&D activity, firms perform too much exploration of the technological space and the amount of loans booms. In turn, a larger flow of loans might imply a waste of resources, due to many unsuccessful R&D projects (Dosi and Lovallo 1997). In other words, finance may tilt the balance between exploration and exploitation in favor of the former. That is beneficial when agents are over-exploiting the existing techniques, but it may become detrimental to growth when resource accumulation via production is not strong enough due to excessive exploration.

To dig deeper into the links between financial depth and economic growth, we run a set of econometric analyses on simulated data to better explore the factors driving the nonlinear relationship between financial depth and growth. First, we control for banking crises, adding to the regression the value of total assets of bankrupted banks (together with its interaction with financial depth). Results show, as expected, that banking crises have a negative effect on growth, but they do not account for the whole detrimental impact of higher levels of financial depth. Second, we further explore the relation between innovation and finance, studying whether different setups for the processes governing technical change and banking sector behavior affect the finance–growth nexus. Overall, our findings are robust to alternative parametrizations, but appear to be more sensitive to variations in the technical-change setups than they do for changes in those governing banking sector behaviors.

Our results have policy implications: the relation between minimum capital requirement and growth is inverted U shaped, and it is possible that more stringent micro-prudential regulations have a positive impact not only on financial stability, but also on long-run growth. Concerning the nominal interest rate, we find that decreasing it has only a slight positive effect on long-run growth while the relation between financial depth and growth is not affected.

The rest of the paper is organized as follows: Sect. 2 discusses some related literature. Section 3 introduces the model while Sect. 4 presents our results. Finally, Sect. 5 concludes.

2 Related literature

Several empirical papers have studied the relationship between finance and economic growth. In a seminal contribution, King and Levine (1993a) find that financial development has a positive effect on growth (see also Rajan and Zingales 1998; Levine et al. 2000; Beck et al. 2000; Beck and Levine 2004). Furthermore, Bodenhorn (2016) shows that the financial system was important in the history of the USA because of the role it played in mobilizing savings, allocating and controlling capital, and mitigating opportunism. The activity of the financial sector can promote growth also through banking integration (Arribas et al. 2017), deregulation (Jerzmanowski 2017), and financial development, via the production of new ideas (Madsen and Ang 2016).

On the theoretical side, Levine (2005) lists five channels through which the financial system can entail positive effects on growth: (i) producing, processing, and collecting information in order to allocate capital to the most profitable firms (Boyd and Prescott 1986; King and Levine 1993b; Greenwood and Jovanovic 1990); (ii) monitoring and improving corporate governance to induce managers to maximize firm value (Stiglitz and Weiss 1983; Bencivenga and Smith 1993; De la Fuente and Marín 1996); (iii) facilitating trade, hedging, and pooling of risk to enhance resource allocation (Levine 1991; Allen and Gale 1997; Acemoglu and Zilibotti 1997); (iv) pooling and mobilizing savings for investments reducing financial frictions (Sirri and Tufano 1995; Acemoglu and Zilibotti 1997); and: v) fostering specialization and easing the exchange of goods and services (Greenwood and Smith 1997).

The issue whether more finance implies more growth, however, has not been settled yet. Indeed, many empirical contributions find mixed or negative impact of finance on long-run growth (Stolbov 2017; Capolupo 2018; Nyasha and Odhiambo 2018). In particular, Kaminsky and Reinhart (1999) and Schularick and Taylor (2012) document that an increase in credit is a good predictor of banking crises, which in turn dampen growth. Furthermore, Kneer (2013) and Cecchetti and Kharroubi (2018) show that misallocation of skilled workers and crowding out of the real activity may occur when the financial sector is too big.

Loayza et al. (2018), reviewing contributions on the topic, interpret the contradicting evidence arguing that a deeper financial sector lets emerge a trade-off between higher growth and higher risk of crisis. At the same time, a growing body of literature (Beck et al. 2012; Cecchetti and Kharroubi 2012; Law and Singh 2014; Arcand et al. 2015; Benczur et al. 2017) provides evidence for a vanishing effect of financial depth on growth leading, eventually, to an inverted U-shaped relation between finance and growth. In particular, finance has a positive marginal effect on growth (Levine 2005) up to a certain degree of financialization. Beyond that threshold, an increase in financialization chokes the real economy, thus exerting a detrimental effect on growth. Misallocation of skilled workers and crowding out of real activities may account for such a negative effect. Other possible mechanisms are highlighted in the agent-based literature. For instance, a large financial sector may hamper economic performances because of: the higher risk of bankruptcy entailed by the resulting financial fragility of firms and banks (Cincotti et al. 2010; Riccetti et al. 2016) or firms misallocating resources (Dosi et al. 2013).

In this paper, we complement those explanations, showing that when the banking sector weakens financial constraints by supplying increasing amounts of loans, the balance between exploration of new technologies and exploitation of existing ones is tilted. Indeed, when exploitation rates in the economy are relatively low, increasing loans delivers higher levels of growth. Conversely, when exploration rates take off, more finance typically means more unsuccessful R&D projects, with a consequent waste of resources and lower growth.

3 The model

We build upon Fagiolo and Dosi (2003) to study an economy evolving over finite time steps, indexed by $t = 0, 1, \ldots, T$. In the original FDM model, the economy is populated by N_f firms located on a two-dimensional boundaryless lattice, whose nodes are defined by a pair of coordinates (x, y). The lattice represents the (unbounded) technological space.[2] Each node can be empty (in the metaphor, *sea*) or occupied, i.e., an *island*.

Islands are technologies that firms can employ to produce a homogeneous good. Islands (indexed as $j = 1, 2, \ldots$) are scattered randomly across the nodes of the lattice according to a i.i.d. Bernoulli distribution with $\text{Prob}\{(x, y) = island\} = \pi$. The higher the π, the larger the technological opportunities in the economy (Dosi 1988; Dosi and Nelson 2010). Island locations are not known ex-ante by firms.

Each island j located in (x_j, y_j) is characterized by a productivity coefficient $s_j = s(x_j, y_j) > 0$, equal to the output that the island can produce if only one firm is employing that technology. In general, both total and average island outputs are increasing in the number of firms employing that technology.

In every time period, any agent can be in one out of three mutually exclusive states: (i) miner (mi); (ii) imitator (im); and (iii) explorer (ex). Miners are located on islands

[2] We do not attach any meaning to the x and y dimensions. A 2-dimensional lattice is chosen only for descriptive reasons.

and produce a homogeneous good (i.e., the numeraire of the economy) using the technology provided by the island where they live. We assume that every firm can employ only one technology in any given time period, whereas the same technology can be used by many firms (i.e., islands can accommodate many firms, but any firm can occupy only one island at any time). Explorers look for new, previously unknown, islands traveling across the lattice. If they find one, they start producing there and the new technology enters the set of already known islands. Imitators move toward an already known island to ultimately adopt its technology and start producing there. In the metaphor, miners produce mastering existing technologies, imitators engage in technologic adoption, spreading the diffusion of more productive techniques, whereas explorers try to discover new technologies by investing in risky R&D activities.

At time $t = 0$, only one island is known and is located for simplicity in the origin $(0, 0)$. We assume that, on average, the productivity coefficient of an island is increasing in the distance of that island from the origin, where the distance is defined as the Manhattan metric over the lattice. Therefore, we assume that on average the farther the one goes from node $(0, 0)$, the more efficient are the technologies that can be found.

We extend the original model introducing a banking sector. We assume that there exist N_b banks indexed as $l = 1, 2, \ldots, N_b$. Banks are not located on the lattice. At time $t = 0$, each agent is assigned to one (and only one) bank in such a way that each bank has the same number of agents connected to it (i.e., there are no ex-ante differences among banks).

As we explain in more detail below, firms can produce output, consume, and save. They deposit their savings in the bank and apply for a loan when they need funds to finance their innovation and imitation activities. Finally, they are also the shareholders of the banks and receive dividends in case of profits.

3.1 Timeline of events

The model is simulated across discrete time steps. We briefly sketch here the sequence of events taking place at any t, which we describe in more detail in the next subsections.

1. Banks provide loans by opening credit lines to firms whose applications were positively evaluated in period $t - 1$. If a bank ends up with a profit at $t - 1$, dividends are paid out;
2. Bankrupted firms at $t - 1$ are reintroduced as miners on the island they left;
3. Miners produce, consume, save, and pay back any existing loan;
4. Banks declared bankrupt at $t - 1$ are recapitalized by shareholders;
5. Explorers continue their journey in search of new islands, consuming a fraction of the resources deposited on their bank accounts.
6. Miners decide whether to become explorers. In case they do, and if their own resources are not enough to finance exploration, they apply for a loan;
7. Imitators continue to travel toward their destination consuming a fraction of the resources deposited on their bank accounts.
8. Miners decide whether to become imitator, and, if their own resources are not enough to finance the travel, they apply for loans;

9. Firms that run out of resources are declared bankrupt and removed from the lattice. Banks that end up with negative equity or run out of liquidity are declared bankrupt and liquidated;
10. Firms connected to a non-bankrupt bank and without outstanding loans invest a fraction of their production in the bank's capital;
11. Banks evaluate loan applications and supply the loans they decided to provide.

3.2 Production

At time $t = 0$, all firms are miners and live in the initial island located at the origin of the lattice. We assume that its productivity coefficient is $s_1 = s(0, 0) = 1$.

More generally, a miner i located at time t on island j with coordinates (x_j, y_j) produces an output given by:

$$q_{i,t}^{j} = s(x_j, y_j)m_t(x_j, y_j)^{\alpha-1}, \tag{1}$$

where $m_t(x_j, y_j)$ is the number of miners located on island j at time t and $s(x_j, y_j)$ is the j's productivity coefficient. Total production of island j is then equal to:

$$Q_t^j = s(x_j, y_j)m_t(x_j, y_j)^{\alpha},$$

whereas the total output of the economy (GDP) at time t reads:

$$Q_t = \sum_j Q_t^j.$$

Firms consume a share $c \in (0, 1]$ of their production and save the rest.[3] As in the original FDM, α regulates the regime of returns to scale in production. In our analysis, we will focus on a regime which is increasing at the technology (island) level, i.e., $\alpha > 1$. In this way, we can account for knowledge-accumulation effects, like learning by doing (Arrow 1971), and economies of agglomeration (Fujita and Thisse 2013), see also Fagiolo and Dosi (2003) and Fagiolo (2000).[4]

3.3 Innovation

In each period t, any firm i who is currently mining on island j can decide to give up production and start exploring the lattice around j.[5] If she does so, she becomes an explorer, leaving her current island and searching for a new one. Any miner can be willing to become an explorer during time t, independently on the others, with a constant and homogeneous probability $\varepsilon \in [0, 1]$. Thus, ε can be interpreted as the probability of having a potentially innovative idea.

[3] In the first period, agents allocate a fraction γ_2 of their savings to create the initial equity of the bank.

[4] Nonetheless, in Sect. 4.4 we test the consequences of different returns to scale regimes.

[5] This assumption is made for consistency with the original FDM. In reality, firms do not stop production while performing R&D and we tested the consequences of production during sailing in "Appendix A." Overall our results are not qualitatively affected.

Unlike what happened in the original model, the per-period cost of exploration $C_{i,t}$ is now defined in terms of foregone consumption:

$$C_{i,t} = c\, s(x_j, y_j) m_t(x_j, y_j)^{\alpha - 1},$$

where $c \in [0, 1]$ is the share of production consumed.

Since the probability of finding an island is π, the expected exploration cost (E_i^{ex}) is equal to:

$$E_i^{\mathrm{ex}} = \frac{C_{i,t}}{\pi}. \tag{2}$$

If agent i's savings are larger than E_i^{ex}, she starts sailing; otherwise, she applies for a loan in her bank (more in Sect. 3.5).[6]

Explorers move uniformly at random across the lattice. In each time period, they explore one (and only one) node out of the four located close to the starting node (i.e., they can only move up, down, left, or right). The new node can be either "sea" (with probability $1 - \pi$) or "island" (with probability π). In the first case, firm i continues to be an explorer and her searching activity goes on. In the second case, the explorer finds an island, and a new technology is discovered. The explorer stops her search and becomes a miner in the newly discovered island.[7]

The productivity of any newly discovered island k is equal to:

$$s(x_k, y_k) = (1 + W)\Big(|x_k| + |y_k| + \phi q^{j}_{i,\tilde{t}} + \omega\Big), \tag{3}$$

where W is drawn from a Poisson(λ) and captures low-probability radical innovations; ω is drawn from a $N(0, 1)$ and accounts for small productivity shocks; and $\phi \in (0, 1)$ is a parameter measuring the strength of the "memory" of the explorer. In other words, explorer i carries the experience coming from her previous activity as miner in j until time $\tilde{t}$. This controls for the cumulativeness of technical change, one of the main components of technological progress (Dosi 1984). Note also that farther the island is away from the initial one (located at the origin of the lattice), the higher its expected productivity. Moving uniformly at random, explorers may also go toward islands with lower expected productivity. Such form of undirected exploration is aimed at mimicking the deep uncertainty that pervades innovative activities (see, e.g., Dosi 1988; Dosi and Egidi 1991; Dosi and Nelson 2010; Teece et al. 2016).[8] If the explorer runs out of funds while sailing, she declares bankruptcy and comes back to the island

[6] Here one can imagine that more "risk averse" explorers would like to have larger savings, or borrow more resources, than the expected exploration cost. That is, they could apply a sort of safety buffer. We test the consequences of this assumption in "Appendix A." Our results are not significantly affected by such refinement. Notice also that such dependence of exploration upon savings, combined with the way in which banks provide loans (see Sect. 3.5), makes the probability that a firm starts exploring increasing in the amount of savings.

[7] The same happens if the explorer arrives, by chance, to an already known island.

[8] One could relax such an assumption allowing firms to move only in the directions where the productivity of the new technologies should be higher than the one they currently master. We will consider this setting in future versions of the model.

she left.[9] At the same time, if a newly discovered island has a lower productivity than the one the explorer left, the new technology is adopted anyway.[10]

3.4 Imitation

Agents can also adopt existing technologies. Miners can indeed become imitators through the process of diffusion of information about the productivity coefficient of existing islands. More specifically, in each time step each miner working on j can receive a signal from any other (currently employed) islands. The probability $w_{j,k,t}$ of receiving a signal from island $k \neq j$ located at (x_k, y_k) for a miner in island j is increasing in the number of miners $m_t(x_k, y_k)$ currently working on k and exponentially decreasing with the Manhattan distance in the lattice between j and k, that is,

$$w_{j,k,t} \propto m_t(x_k, y_k) \exp\{-\rho(|x_j - x_k| + |y_j - y_k|)\}, \tag{4}$$

with $\rho \geq 0$.

Suppose that a miner i working on j receives $z > 1$ signals from islands $j_1, \ldots, j_z$ different from j. Then i decides to become an imitator if:

$$\max_h \left\{ s(x_{j_h}, y_{j_h}) \right\} > s(x_j, y_j), \tag{5}$$

that is, if there exists a signal coming from another island whose productivity coefficient is strictly larger than the one currently experienced. Otherwise, firm i keeps producing on island j. The island j^*, located at (x_{j^*}, y_{j^*}), which maximizes the left-hand side of (and satisfies) Eq. (5) is the technology adopted by i.[11]

Imitation takes time and is a costly (but certain) activity. Firm i takes exactly $|x_j - x_{j^*}| + |y_j - y_{j^*}|$ time steps before starting to produce as a miner on j^* (i.e., they move toward j^* one step per time period, following the shortest path in the lattice).[12]

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[9] One could imagine that bankrupt explorers should be more penalized, e.g., letting them go back to the origin or introducing some form of bankruptcy cost they should pay when restarting production. However, the cumulation of knowledge and the dynamic increasing returns which are generated while the explorer was sailing let the bankrupt agent fall behind with respect to the technological frontier. This constitutes already a fairly large penalization.

[10] The probability of such an outcome is negligible, as the productivity of a newly discovered island is linked to the last production carried out by the explorer. For this reason, we make this assumption for keeping the setting as simple as possible. However, in future versions of the model we will consider a more sophisticated setting in which an explorer can continue to sail when she arrives on an already known island with lower productivity, or she can come back to her initial island.

[11] In the case of multiple maxima, miner i chooses one of them at random.

[12] Also in this case we assume that imitators do not produce during sailing for consistency with the FDM. An analysis of the consequences of production during sailing can be found in "Appendix A." See also footnote 5.

Unlike in the exploration case, the per-period cost of sailing C^{im} is now certain, as imitation is a safe activity.[13] It reads:

$$C_i^{\mathrm{im}} = \left[c\, s(x_j, y_j) m_t(x_j, y_j)^{\alpha-1}\right] (|x_j - x_{j^*}| + |y_j - y_{j^*}|). \qquad (6)$$

If firm i savings are not enough, she tries to get credit from her bank.[14]

3.5 Banks and credit

As mentioned above, we extend the original FDM introducing a banking sector in the economy. Miners can apply for a loan to their bank to explore or imitate. We assume that each bank l holds a total supply of credit $L_{l,t}^{\mathrm{sup}}$ defined as:

$$L_{l,t}^{\mathrm{sup}} = \frac{Eq_{l,t}}{\chi} - L_{l,t},$$

where $Eq_{l,t}$ is bank equity, $0 \leq \chi \leq 1$ is the minimum capital requirement, and $L_{l,t}$ is the stock of loans of the bank.

As credit market is characterized by imperfect and asymmetric information (see, e.g., Stiglitz and Weiss 1981), banks do not know if the requested loan will finance an imitation journey or a riskier exploration venture.[15] As a consequence, banks simply allocate credit to applicants ranking them with respect to their loan–savings ratio in ascending order, until the bank has resources to fully satisfy a client's application. Thus, savings act as a sort of "collateral" that banks use to mitigate the inefficiencies generated by *ex-ante* information asymmetry. This is in line with the empirical findings of Berger et al. (2011). Note that some firms may end up being credit rationed. Finally, the bank charges an homogeneous interest rate $r > 0$ to every client.

Firms who want to become explorers or miners and got their loan application accepted start traveling. During each traveling time step, agents withdraw the per-period consumption from their bank.

If they succeed in reaching a new island or their target for adoption, they become miners there and start paying back their loans (plus the interests) using the savings they are able to generate until the loan is completely repaid. While a firm has a standing loan, no exploration or imitation is allowed.

[13] One can also assume that adoption should be further favored by reducing the time and hence the cost, it takes to be performed. We analyze such scenario in "Appendix A." Our results are robust to lower time for adoption.

[14] We assume that the per-period share of production c consumed for imitation equals that for exploration.

[15] Since "asymmetric information is a defining characteristic of credit markets" (Dell'Ariccia 2001, see also Bhattacharya and Thakor 1993; Van Damme 1994), this is the only viable way to introduce it in the model. Indeed, given our simple setting, if banks were able to distinguish between explorers and imitators, their information would be perfect. Nonetheless, we investigate the role of information asymmetry in Sect. 4.4.

Firms can go bankrupt during exploration. In that case, the bank faces a loss and decreases its equity by the amount of the loan provided to the explorer.[16] If bank's equity becomes negative, then the bank goes bankrupt. If a failed bank has any remaining liquidity, it will distribute it first to the depositors according to their net position[17] and then to shareholders according to their capital share. Then, in the next period, a new bank is created with the capital provided by the old shareholders. More specifically, each agent bestows a fraction γ_2 of her savings to the new bank. As there are costs in creating the new bank, only a fraction $0 \leq \zeta < 1$ of the new resources form its equity.

At the end of any time step, banks may obtain profits. In that case, a fraction ξ of profits are distributed to the shareholders as dividends. The rest will increase the equity of the bank. Finally, miners who do not have any outstanding debt transfer a fraction $\gamma_1 \in (0, 1]$ of their savings to increase the equity of the bank.

4 Simulation results

As it happens almost always with stochastic, agent-based, dynamic systems, the model described above does not have a closed-form analytical solution for the probability distributions of its long-run states. Therefore, simulations are required to get quantitative insights on the statistical behavior of the model.[18]

We start from a baseline parametrization of the model, for which we generate a sample of 3000 Monte Carlo (MC) replications. Such a sample size has been selected so as to ensure convergence of MC moments for the distributions of the statistics of interest.[19]

The baseline parametrization, reported in Table 1, has been chosen so as to replicate a benchmark setup of the original FDM. In particular, the parameters $(\epsilon, \phi, \pi, \rho, \lambda, \alpha)$, as well as the population size N, have been all set according to a high-growth scenario of the FDM (without banks). Parameters not featured in the FDM, whenever possible, are set to realistic values. For example, the value for χ is in line with Basel II requirements.[20]

In what follows, we first study whether in the baseline parametrization the time series of aggregate output generated simulating the model display statistical properties found in real GDP data. Then, we explore departures from the baseline parametrization.

[16] Since a bankrupt agent may hold bank equity shares, we assume for simplicity that in such a case the shares are redistributed to the other shareholders proportionally to their positions. Investigating the effects of bank ownership structure goes beyond the objectives of the present analysis.

[17] We define net position as the difference between agent's deposit and outstanding loan. If liquidity is not enough to satisfy depositors, then it is distributed proportionally to net positions. A firm with negative net position does not receive anything.

[18] The source code of the model, written in C++, is available upon request.

[19] All our results do not significantly change if one increases Monte Carlo sample sizes. Extensive tests show that the MC distributions of the statistics of interest are sufficiently symmetric and unimodal. Thus, we can use MC sample averages to get meaningful synthetic indicators.

[20] The Basel II capital requirement is 8%, while in our baseline parametrization we fix it to 10%. Our choice captures the additional capital buffer that risk averse banks hold in order to reduce their solvability risk.

Table 1 Baseline parametrization

Parameter	Value	Description
T	500	Number of time periods in each run
N_f	100	Number of agents
N_{b}	5	Number of banks
π	0.1	Probability that a node is an island
ϕ	0.5	Strength of cumulative learning effect
λ	1	Intensity of high-productivity jumps
α	1.5	Returns to scale parameter
ρ	0.1	Degree of locality of signals
ε	0.1	Probability that a miner becomes an explorer
c	0.7	Share of production consumed
γ_1	0.01	Share of savings invested in banks' equity
γ_2	0.5	Share of savings devoted to create a new bank
χ	0.1	Minimum capital requirement
r	0.1	Baseline interest rate
ζ	0.1	Bank setup costs
ξ	0.15	Share of banks' profits paid as dividends

This allows us to investigate the impact of banks and credit on the long-run growth of the economy. Finally, we analyze the possible nonlinear relationships between financial depth and growth.

4.1 Empirical validation

We begin considering the aggregate output time series generated by a typical simulation run under the baseline parametrization defined above.[21] Figure 1 shows that the model is able to account for endogenous self-sustaining growth (in line with Fagiolo and Dosi 2003). We then study whether aggregate output time series display statistical properties akin to those exhibited by empirically observed GDP time series. More specifically, we ask whether: (i) the log of aggregate output time series is integrated of order 1; (ii) output growth rate series are stationary with positive and fast-decaying autocorrelations of output growth rates; (iii) aggregate output fluctuations are persistent.

In order to test for non-stationarity of aggregate output and stationarity of its growth rates, we perform a battery of augmented Dickey–Fuller (ADF) tests on each time series of the simulated Monte Carlo sample. For each test performed, we record whether the null hypothesis of unit root is rejected (or not), setting the significance level (alpha) at 5%. We find that, in the baseline parametrization, aggregate output time series are integrated of order 1 and difference stationary. Indeed, the frequency of acceptance of ADF tests performed on the log of aggregate output ranges between

[21] For a critical discussion of empirical validation of agent-based models, see Fagiolo et al. (2017).

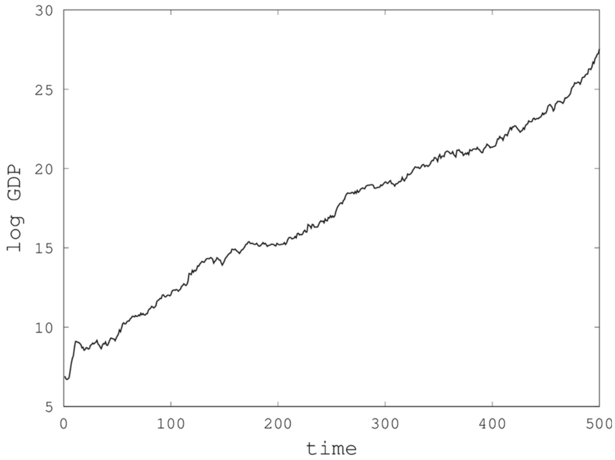

Fig. 1 Representative time series of log GDP ($\log(Q_t)$) generated by the model under the baseline parametrization in Table 1

94% (in the case a drift is introduced in the test specification) and 100% (when neither a drift nor a trend is included). Conversely, no matter the ADF test specification, the ADF test is always rejected for simulated time series of output growth rates.

We turn now to analyzing the autocorrelation patterns displayed by the growth rates of aggregate output. Figure 2 plots MC averages of growth rates (left panel) and MC averages of the autocorrelation function (right panel), which we have separately estimated in each Monte Carlo run. In line with the empirical evidence (Cochrane 1988), autocorrelations are positive for the first lags, and then, they fast decay to values not significantly different from zero—according to Bartlett bands.

Finally, we consider the nonparametric measures $\hat{V}^k$ and $\hat{A}^k(1)$ of persistence in output fluctuations used in Campbell and Mankiw (1989) and Cochrane (1988),[22] defined as:

$$\hat{V}^k = \frac{T-k}{T}\left[1 + 2\sum_{j=1}^{k}\left(1 - \frac{j}{k+1}\right) r_j\right],$$

where r_j is the lag j sample estimate of the autocorrelation function, and

$$\hat{A}^k(1) = \sqrt{\frac{\hat{V}^k}{1 - r_1^2}}.$$

Table 2 shows the MC averages and standard errors of the two statistics computed over our artificial sample. The estimates are significantly larger than one for every time horizon considered, confirming that the model is able to produce aggregate output fluctuations with persistence levels similar to those observed in real-world GDP data.

The foregoing results suggest that, at least in the baseline parametrization, the model is able to generate aggregate output time series that are statistically not distinguishable

[22] See Fagiolo and Dosi (2003) for more details.

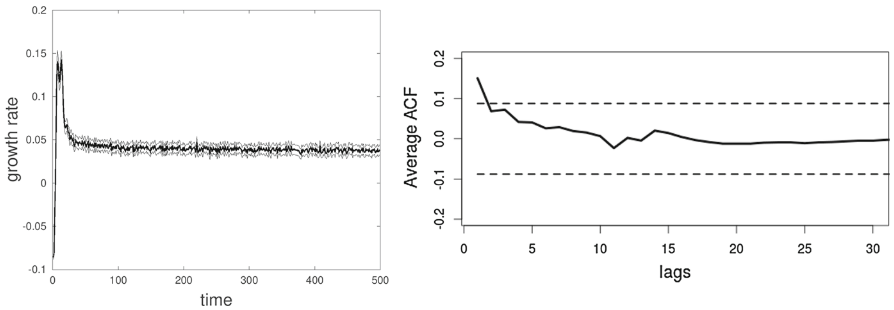

Fig. 2 Left: MC average growth rates with confidence bands set to three standard errors away from Monte Carlo sample averages. Right: MC average growth rate autocorrelation function where dotted lines are 95% Bartlett confidence bands. Monte Carlo sample: 3000 replications

Table 2 MC averages of the estimated $\hat{V}^k$ and $\hat{A}^k(1)$ with standard errors in parenthesis. Monte Carlo sample: 3000 replications

	$K = 10$	$K = 20$	$K = 30$	$K = 40$	$K = 50$
$\hat{V}^k$	1.616448	1.706264	1.670570	1.613766	1.563051
	(0.006743)	(0.009113)	(0.010663)	(0.011879)	(0.012843)
$\hat{A}^k(1)$	1.281972	1.311785	1.292527	1.264568	1.239006
	(0.002891)	(0.003691)	(0.004266)	(0.004755)	(0.005156)

from their real-world counterpart. A similar conclusion holds, in general, whenever the model is able to produce self-sustaining endogenous growth. This happens—as in the original model—for quite a large subset of the whole parameter space. As discussed in Fagiolo and Roventini (2017), the fact that an agent-based model is empirical validated for a non-trivial subset of all its possible parameter constellations is a necessary prerequisite to subsequently ask what-if type of questions and to perform economic policy exercises. At the same time, the model is quite abstract and stylized. Thus, instead of attempting at calibrating it, we will focus on the theoretical analysis through several sensitivity exercises.[23]

4.2 The impact of credit on output growth and volatility

We begin asking whether introducing banks in the FDM has a positive impact on aggregate output. We study two setups, one with banks providing credit to firms and the other without banks, i.e., a sort of "autarkic" setting where firms can rely only on their cumulated cash flows to finance innovation and imitation activities.

We compare the performance of the simulated economy in the two setups. We focus on the behavior of (the log of) aggregate output time series, as well growth rate output volatility. To measure volatility, we build the time series of the standard deviation of

[23] We thank an anonymous referee for having pointed out this.

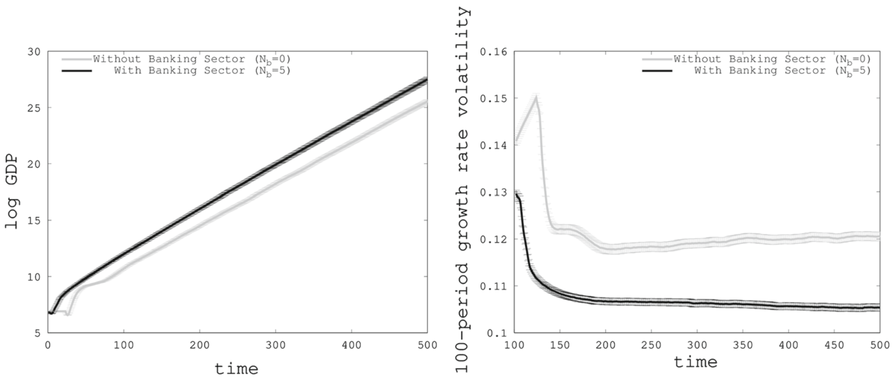

Fig. 3 MC averages of log GDP and 100-period growth rate volatility with and without banking sector. Confidence bands are set to three standard errors away from Monte Carlo sample averages

aggregate output growth rates in the 100 periods preceding the current time step t, i.e.,

$$\sigma_t^{100}(g) = \sqrt{\sum_{\tau=0}^{99} \frac{\left(g_{t-\tau} - \mu_t^{100}(g)\right)^2}{100}}, \tag{7}$$

where $g_t = \log Q_t - \log Q_{t-1}$ and $\mu_t^{100}(g) = (\log Q_t - \log Q_{t-100})/100$.

The results of our experiments are presented in Fig. 3. We observe that the presence of a banking sector allows for higher growth and lower volatility. This is so because, in the model, growth stems from a right balance between the resources devoted to producing by exploiting the current set of technologies, introducing new techniques, and diffusing the new technologies. The credit activity of banks removes the resource constraint preventing agents from discovering new technologies and imitating better ones. This in turn puts the economy on a virtuous growth path. The growth-enhancing effect of credit is particularly relevant in the first phases of economic development, when firms need to accumulate enough resources to start exploring the technological space (see the left panel of Fig. 3). The discovery of more productive islands allows for imitation, and this induces the diffusion of better technologies and faster growth. Even after the economy stabilizes on a steady growth path, the output gap between the scenario with banks and the “autarkic” setup keeps on increasing, suggesting that the resource constraint does affect firms when the financial sector is not present.

Let us now consider the impact of banks and credit on output volatility. Figure 3 shows that volatility is typically high in the first periods of the simulation and then quickly converges to its long-run stable value. This points out that the model gets out of its transient phase quite fast and then reaches its long-run stable growth pattern. The presence of banks appears to reduce output volatility. Again, the positive influence of the credit sector stems from the delicate balance between exploration and exploitation, together with the possible emergence of coordination failures. Indeed, when a firm leaves her island, production falls, and output can increase again only when a new (highly productive) island is discovered. If agents move in a coordinated way, a huge drop in output will be followed by spurs of growth when new technologies are discovered and diffused. Banks break such a vicious cycle allowing agents to leave their island smoothly without the accumulation of the resources otherwise needed in the "autarkic" scenario.

4.3 Financial depth, output growth, and volatility

The foregoing first set of experiments suggests that credit and banks have a positive impact on growth. This is in line with many empirical works (King and Levine 1993a; Rajan and Zingales 1998; Levine et al. 2000; Beck et al. 2000).

A natural subsequent question is whether increasing levels of financialization are always beneficial for growth, or if instead they might harm the economy and, when financialization becomes too strong, can possibly trigger crises. In fact, as explained in Sect. 2, nonlinear relationships in the finance–growth nexus have been recently found by several studies.

In the next experiments, we will explore with our model the existence of non-linearities in the relationship between finance and growth. We define financial depth—in line with existing literature (see, e.g., Arcand et al. 2015)—as the amount of outstanding loans over production:

$$\mathrm{FD}_t = \frac{\sum_{l=1}^{N_b} L_{l,t}}{Q_t}. \tag{8}$$

Since loans provided in the current period may take several time steps to affect growth, we consider its 10-period average:

$$\overline{\mathrm{FD}}_t^{10} = \frac{\sum_{\tau=0}^{9} \mathrm{FD}_{t-\tau}}{10}. \tag{9}$$

In our regression exercises, the dependent variable is the 10-period output growth rate, defined as:

$$G_t^{10} = \log(Q_t) - \log(Q_{t-10}). \tag{10}$$

To avoid any possible endogeneity issue, we use as a covariate the average financial depth with a ten-period lag (i.e., $\overline{\mathrm{FD}}_{t-10}^{10}$), together with its square.

We build a Monte Carlo sample considering 3000 independent runs, wherein we record $\overline{\mathrm{FD}}_t^{10}$ and G_t^{10} for the last 300 periods of the simulations to avoid any possible transient behavior. In this way, we have a balanced panel of 29×3000 observations.

To begin with, we graphically explore the links between financial depth and GDP growth considering the unconditional relationship between the deciles of the average financial depth pooled distribution and the corresponding average 10-period GDP growth rate. Results are summarized in Fig. 4. In line with the empirical literature (Cecchetti and Kharroubi 2012; Law and Singh 2014; Arcand et al. 2015), 10-period output growth presents an inverted U-shaped relation with respect to financial depth. Indeed, until the fifth decile, financial depth spurs output growth. Then the relation

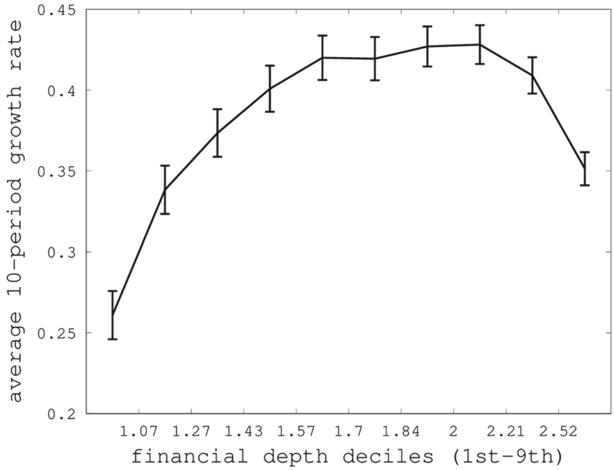

Fig. 4 MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\mathrm{FD}}_{t-10}^{10}$ under the parametrization in Table 1.Confidence bands are set to three standard errors away from Monte Carlo sample averages

stabilizes, but for higher financial depth levels finance harms the long-run performance of the economy.

We now explore a conditional model to better understand the relationship between financial depth and growth. We employ our balanced panel to run fixed-effect regressions of growth rates on average financial depth and average financial depth squared (as in Arcand et al. 2015).

More specifically, the simple econometric model that we estimate reads:

$$G_{n,t}^{10} = \beta_0 + \beta_1 \overline{\mathrm{FD}}_{n,t-10}^{10} + \beta_2 \left(\overline{\mathrm{FD}}_{n,t-10}^{10}\right)^2 + a_n + u_{n,t}, \tag{11}$$

where the subscript n denotes the Monte Carlo replication; a_n captures a Monte Carlo run-specific effect; and $u_{n,t}$ is the time t error term for run n.

Regression results are reported in Table 3. The results of the econometric exercise confirm the existence of a nonlinear, inverted U-shaped relationship between financial depth and growth.

The underlying mechanism that drives this result is again linked to the dynamic solution of the exploration–exploitation trade-off. When banks provide a relatively small amount of loans, the economic growth is weak as agents may not hold the necessary resources to innovate. Thus, increasing the loan-to-output ratio spurs growth via higher innovation rates and faster technological diffusion. However, as credit keeps on increasing, the higher financialization of the economy fuels the "animal spirits" of the firms. This wastes an excessive amounts of resources in unfruitful exploration instead of producing more output using existing techniques. This in turn slows down output growth.

This intuition is corroborated by the results obtained tuning the parameter governing the propensity to explore (ε) of the agents. Indeed, as Fig. 5 shows, for lower levels

Table 3 Estimates of the econometric model with standard errors in parenthesis

	Dependent variable: $G_{n,t}^{10}$		
	(1)	(2)	(3)
$\overline{\mathrm{FD}}_{n,t-10}^{10}$	0.3207***	0.3441***	0.3441***
	(0.0106)	(0.0106)	(0.0106)
$\left(\overline{\mathrm{FD}}_{n,t-10}^{10}\right)^2$	−0.0635***	−0.0670***	−0.0671***
	(0.0026)	(0.0026)	(0.0026)
$\overline{\mathrm{ta}}_{n,t-10}^{b,10}$		−0.5321***	−0. 5373***
		(0.0192)	(0.0612)
$\overline{\mathrm{ta}}_{n,t-10}^{b,10} \times \overline{\mathrm{FD}}_{n,t-10}^{10}$			0.0028
			(0.0307)
Constant	0.0368***	0.0412***	0.0414***
	(0.0104)	(0.0104)	(0.0105)
Observations ($T \times N$)	29×3000	29×3000	29×3000
R^2	0.076	0.084	0.084
Adjusted R^2	0.041	0.052	0.052
F Statistic	2.298***	2.575***	2.574***
	(df = 3001, 83998)	(df = 3002, 83997)	(df = 3003, 83996)

***p value < 0.01, **p value < 0.05, *p value < 0.1

of ε, the positive effects of bank credit are stronger, whereas for higher propensity to explore, a large banking sector fuels over-exploration and output growth falls almost to the autarky scenario. Relatedly, the effects of financial depth on output growth become increasingly negative as agents are more willing to explore. In Fig. 6, we show how the average 1-period GDP growth rate over the last 300 periods (left panel) and the average financial depth over the last 300 periods (right panel) react to different values of ε. Consistently with the intuitions provided, willingness to explore and financial depth are positively related, implying that a relatively larger financial sector is associated with more exploration. At the same time, banking activity makes the relation between exploration and growth more extreme. This is positive for the economy when innovation is low, while becomes detrimental when the exploration activity grows too much.

Finally, we investigate whether the occurrence of banking crises could be the cause of the negative marginal effect of high values of financial depth on GDP growth. Indeed, when banks lend too much, they become more and more fragile and their bankruptcy risk increases. Since the failure of a bank reduces the amount of available resources for exploration and imitation activities, output growth can slow down.

We control for banking crises by adding the size of bankruptcies as a control when estimating Eq. (11). More specifically, we consider the ratio between the total amount of assets of bankrupted banks (TA_t^b) and output:

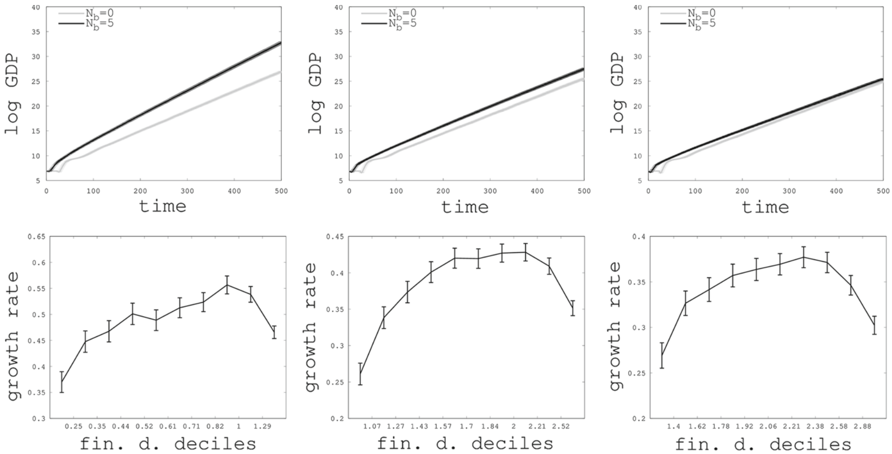

Fig. 5 Propensity to explore parameter ε and economic dynamics. Left: low, $\varepsilon = 0.05$. Mid: baseline, $\varepsilon = 0.1$. Right: high, $\varepsilon = 0.12$. Top: MC average of log GDP with a banking sector ($N_\mathrm{b} = 5$) and without ($N_\mathrm{b} = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\mathrm{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

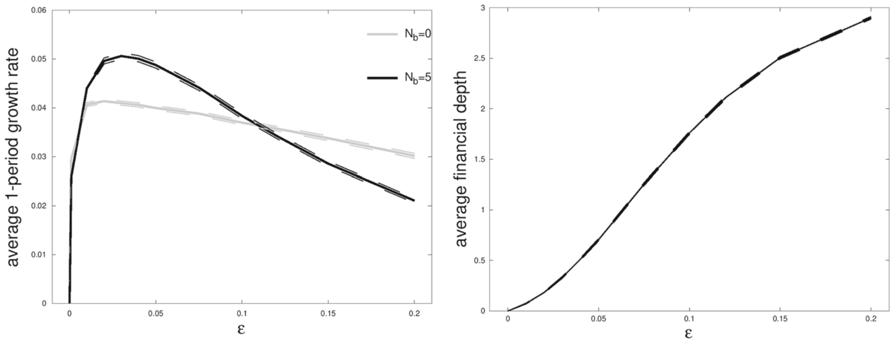

Fig. 6 Left: relation between propensity to explore and the average 1-period GDP growth rate in the last 300 periods. Right: relation between propensity to explore and the average financial depth in the last 300 periods. Solid lines represent Monte Carlo averages over 3000 independent replications while dashed lines represent confidence bands. Confidence bands are set as three standard errors away from Monte Carlo sample averages

$$\mathrm{ta}_t^b = \frac{\mathrm{TA}_t^b}{Q_t}.$$

Thus, we add to the regression its 10-period average, in order to keep consistency with the econometric model in (11):

$$\overline{\mathrm{ta}}_t^{b,10} = \frac{\sum_{\tau=0}^{9} \mathrm{ta}_\tau^b}{10}.$$

We also control for possible interaction effects repeating the estimation with the product between $\overline{\mathrm{ta}}_{t-10}^{b,10}$ and $\overline{\mathrm{FD}}_{n,t-10}^{10}$ among the regressors. In this way, we are checking whether severe banking crises occurring during periods of large financial depth affect in a more disruptive manner long-run growth and modify the relation between $\overline{\mathrm{FD}}^{10}_{n,t-10}$ and $G^{10}_{n,t}$.

We find that the estimates of financial depth coefficients do not basically change (cf. Table 3), while the one related to banking crises is negative and significant. Bank bankruptcies exert a negative effect on future output growth rates, but they cannot explain the nonlinear relationship between financial depth and output. This is in line with the findings of Arcand et al. (2015) about the robustness of the inverted U-shaped relation between the two variables.

4.4 Innovation and credit

Is there any interaction between the technological engine of the model and the amount of fuel provided by bank credit? In order to further explore the connection between innovation and credit, we investigate how our results change when different credit and technical-change parameter constellations are considered.[24]

Technical change. Let us begin with tuning the parameters related to the productivity of the newly discovered innovations, the technological opportunities, the rate of technological diffusion in the economy, and the returns to scale of a technology. For higher levels of innovation cumulativeness (ϕ) and occurrence of radical innovations (λ), the presence of banks further spurs output growth (see Fig. 7). Indeed, in high-productivity scenarios, agents can pay back their debts in fewer periods after they reach a new island. This reduces the risk faced by banks and endows them with more resources for the next exploration phase. In turn, it becomes easier for the banking sector to set the economy on a virtuous combination of exploration and exploitation and increase output growth. The inverted U-shaped relation between growth and financial depth persists. However, in the high-productivity scenario, it becomes flatter, with the turning point shifting leftward. Furthermore, deeper output drops are observed for the highest values of financialization (cf. Fig. 7). This is because, in such a setup, only a fair amount of external finance is needed to maximize growth.[25]

When the probability of discovering a new technology increases (π)—i.e., there are higher innovation opportunities—the banking sector becomes less and less relevant in supporting output growth (see Fig. 8). Higher technological opportunities lessen the amount of R&D investment required to innovate, thus relaxing firm financial constraints. This is confirmed by the relation between financial depth and growth: when opportunities are high, the inverted U shape is more marked and the negative effects of increasing financialization emerge earlier. Looking at the confidence bands of growth rates for the different levels of financial depth, it is interesting to notice how increasing opportunities tend to expand. Hence, introducing new technologies at higher pace makes growth more volatile.

[24] Such an exercise can also be considered as a preliminary—and admittedly very partial—sensitivity analysis of the model. Indeed, we test the robustness of our findings when the value of one or two parameters is changed keeping all the other parameters as in the baseline parameterization in Table 1.

[25] We further tested the effect of lower levels of innovation cumulativeness; overall the results are consistent with the intuition provided here. This analysis can be found in "Appendix A."

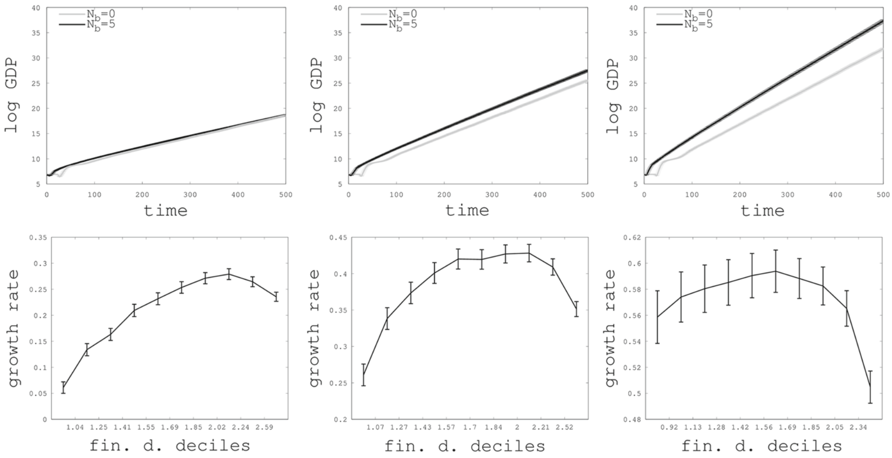

Fig. 7 Productivity scenarios. Left: low, $\phi = 0.3$ and $\lambda = 0.5$. Mid: baseline $\phi = 0.5$ and $\lambda = 1$. Right: high, $\phi = 0.7$ and $\lambda = 2$. Top: MC average of log GDP with a banking sector ($N_b = 5$) and without ($N_b = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\text{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

Next, we investigate technological diffusion occurring in the model via imitation activities carried out by the firms. To do so, we tune the parameter ρ in order to consider different scenarios for the diffusion of information in the economy. Recall that the higher the ρ, the more the information is locally diffused, as the probability of receiving a signal decays faster around the island from which it originates. If technological diffusion is more globally diffused (small ρ's), the positive long-run impact of finance becomes more evident, as agents need resources to imitate (cf. Fig. 9). However, the detrimental marginal effect of an hypertrophic financial sector increases with higher technological diffusion. Indeed, when imitation is more local (large ρ's), the economy needs more technological exploration to sustain growth. When diffusion is instead more global, only few new discoveries are needed and the economy ends up quicker in over-exploration.

Finally, we test how our results change when different regimes of returns to scale at the technology level are considered. Figure 10 shows how technologically increasing returns are necessary to achieve endogenous exponential growth. Indeed, when returns to scale are decreasing or constant, growth rates decrease over time and the presence of a banking sector seems to have a negative effect in the long run. Indeed, while credit lets the economy grow more in the first phases of development because of higher exploration and imitation, discovering or adopting a new technology is not very rewarding because of a lack of dynamic increasing returns.[26] Hence, on the one hand, firms take more time to pay back their loans while, on the other, new technologies have to be continually introduced to sustain growth. Thus, over-exploration becomes a rare event and this explains why high levels of financial depth are no more (or only slightly) detrimental for growth.

[26] Notice also how, from Eq. (1), individual production decreases with the number of miners when $\alpha < 1$.

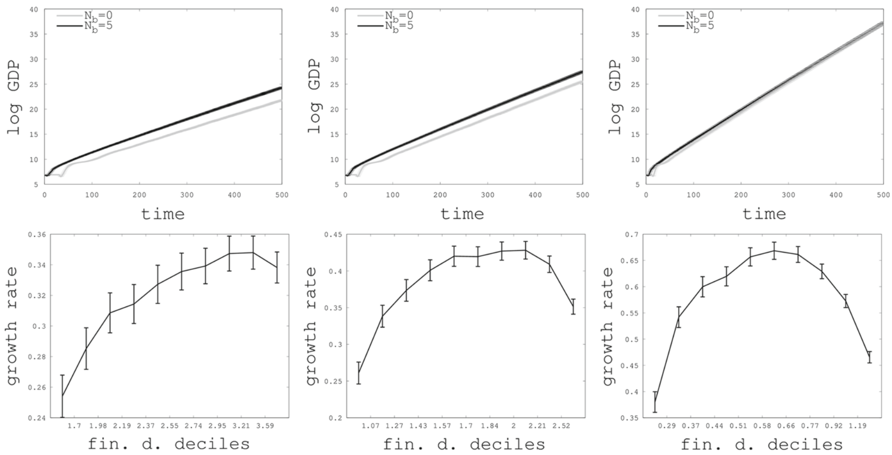

Fig. 8 Innovation opportunities. Left: low, $\pi = 0.075$. Mid: baseline, $\pi = 0.1$. Right: high, $\pi = 0.2$. Top: MC average of log GDP with a banking sector ($N_\mathrm{b} = 5$) and without ($N_\mathrm{b} = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\mathrm{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

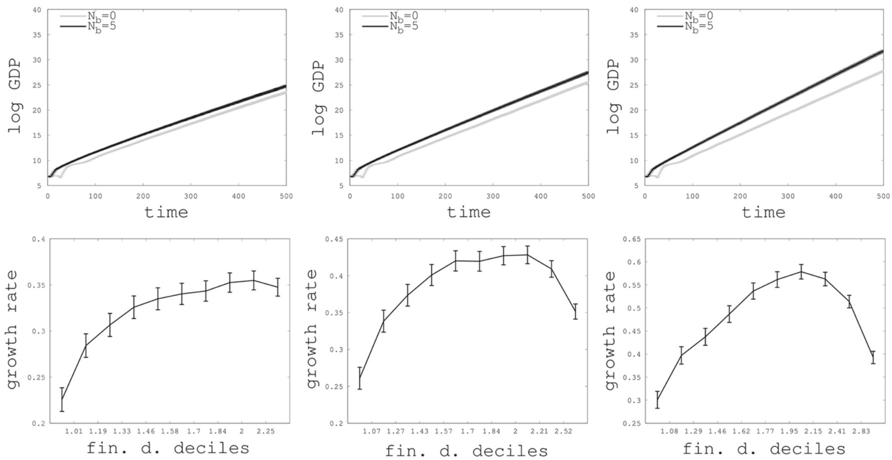

Fig. 9 Technological diffusion. Left: local, $\rho = 0.15$. Mid: baseline, $\rho = 0.1$. Right: global, $\rho = 0.01$. Top: MC average of log GDP with a banking sector ($N_\mathrm{b} = 5$) and without ($N_b = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\mathrm{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

Banking activity We now investigate how simulation results change when different policy scenarios concerning the banking system are considered. More specifically, we focus on the stringency of micro-prudential regulations and the nominal interest rate, two parameters usually influenced by central banks or financial authorities. We also investigate the role of information asymmetries in the credit market analyzing how the results change when banks can discriminate between explorers and imitators. In the

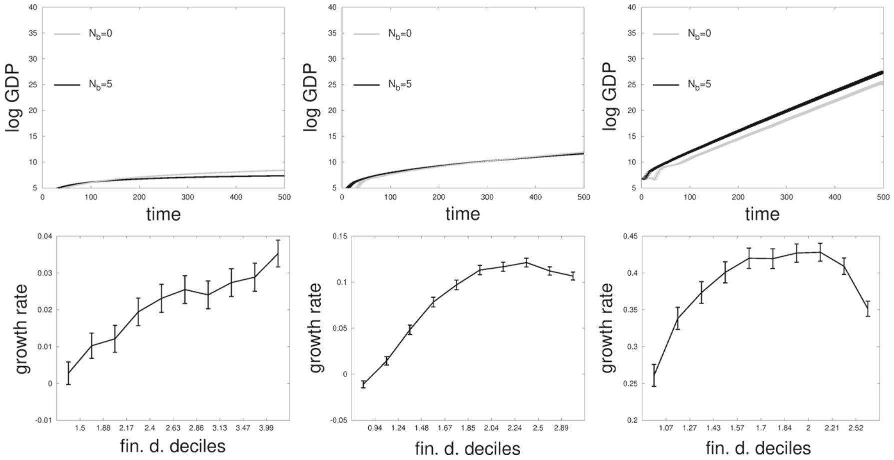

Fig. 10 Returns to scale. Left: decreasing, $\alpha = 0.75$. Mid: constant, $\alpha = 1$. Right: increasing, $\alpha = 1.5$ (baseline). Top: MC average of log GDP with a banking sector ($N_b = 5$) and without ($N_b = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\text{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

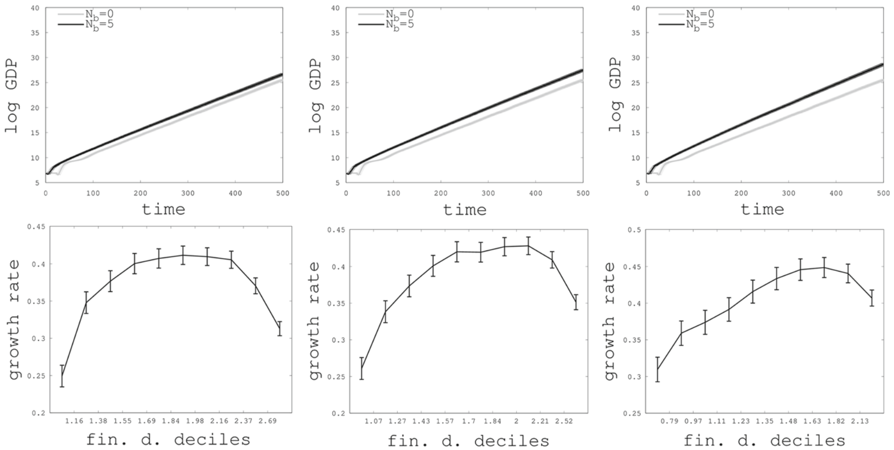

Fig. 11 Minimum capital requirement. Left: low, $\chi = 0.05$. Mid: baseline, $\chi = 0.1$. Right: high, $\chi = 0.2$. Top: MC average of log GDP with a banking sector ($N_b = 5$) and without ($N_b = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\text{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

end, we discuss the robustness of our results to variations in the parameters regulating agent investment in banks' equity.[27]

[27] We also tested how the economy reacts to changes in bank setup costs and in the number of banks. Overall, our results are robust and consistent with the effect of credit on the exploration–exploitation trade-off. For this reason, we do not report such analyses, which are nevertheless available from the authors upon request.

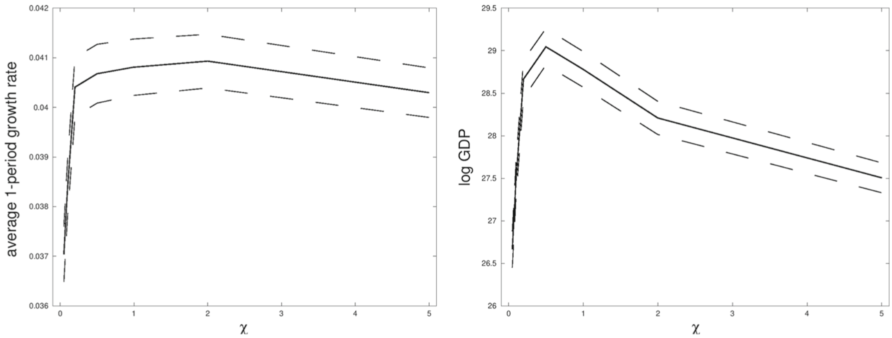

Fig. 12 Left: relation between minimum capital requirement and the average 1-period GDP growth rate in the last 300 periods. Right: relation between minimum capital requirement and log GDP at $t = 500$. Solid line represents the Monte Carlo average over 3000 independent replications while dashed lines represent confidence bands. Confidence bands are set as three standard errors away from Monte Carlo sample averages

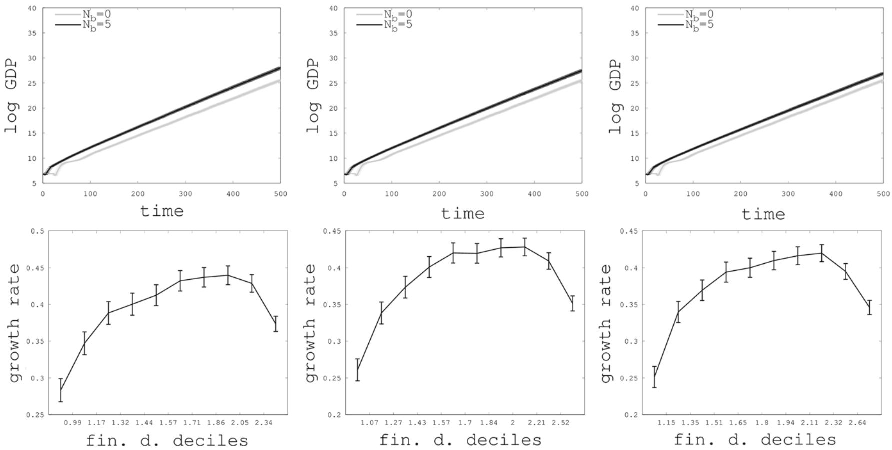

Fig. 13 Interest rate. Left: low, $r = 0.05$. Mid: baseline, $r = 0.1$. Right: high, $r = 0.15$. Top: MC average of log GDP with a banking sector ($N_b = 5$) and without ($N_b = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\mathrm{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

More stringent micro-prudential regulations are obtained in the model increasing the minimum capital requirement χ. Results show that, in a range of values close to the Basel II 8% requirement, increasing χ has a positive impact on long-run growth (see Fig. 11). Indeed, restraining credit supply reduces the possibility of over-exploration, thus reinforcing the balance sheets of banks. This is also confirmed by the relation between financial depth and growth. However, we have to notice that in the limit of an extremely high requirement, which basically eliminates credit, GDP growth converges to the levels achieved without a banking sector. Hence, the relation between χ and growth is inevitably inverted U-shaped and an "optimal value" of minimum capital exists, see Fig. 12 left panel. Such trade-off becomes even more evident if one considers log GDP levels reached at time 500 (Fig. 12 right panel). The difference between the two curves highlights the important role credit plays in the first phases of economic development. The results in Fig. 11 are driven by the fact that the values considered concern the increasing part of the inverted U-shaped relation, see Fig. 22 in "Appendix A" for an analysis of the decreasing side of the relation.

The economy is instead less reactive to changes in the interest rate (r). This is probably because, on the one hand, higher interest rates extend the period required by firm to pay back their debt, reducing the long-run output level. At the same time, firm innovation and imitation decisions in the model do not rely upon the interest rate; hence, a reduction in the cost of external funding does not stimulate very much the economy (Fig. 13).

Concerning the role of informative inefficiencies, we compare the results under the baseline setting with those obtained when banks can discriminate between imitation and exploration applications and apply different interest rates. In particular, we impose that banks prefer to serve all the imitators before devoting resources to explorers. Within each class, applications are ranked in ascending order according to the loan–savings ratio. We assume that the interest rate for imitators is 0.07, while the one applied to explorers is 0.12. Figure 14 shows the comparison. As one can notice, long-run growth is slightly higher when banks can discriminate applications. The inverted U-shaped relation between financial depth and growth becomes less strong, but it is still present. This is given to the fact that, restraining the amount of resources devoted to risky projects, over-exploration becomes less likely.

Finally, Figs. 15 and 16 show that, overall, our qualitative results are robust to variations in the parameters γ_1 and γ_2. It is interesting to notice how long-run growth is negatively affected when agents devote too much resources to banks' equity. The reason is twofold. On the one hand, the erosion of savings lets firms rely more on loans and this substitution of internal finance with external finance makes the economy more fragile. On the other, the expansion in banks' equity translates in more resources to provide loans, which increases the likelihood of experiencing an excess of exploration.

5 Conclusions

In this paper, we have investigated the interactions between innovation, credit, and growth in a supply-side model of industry dynamics. To do so, we have introduced a banking sector in the endogenous growth agent-based model developed in Fagiolo and Dosi (2003). We have explicitly taken into account the effects that finance has on innovation and imitation activities of firms, as well as on the long-run performance of the economy.

Simulation results show that banks, by providing loans, are able to foster technological innovation and diffusion, thus improving long-run economic growth. Credit allows indeed to achieve a better balance between the technological exploration and exploitation activities of firms. However, credit and technical change coevolves with possibly nonlinear effects. In line with the empirical evidence (Cecchetti and Kharroubi 2012; Law and Singh 2014; Arcand et al. 2015), we find an inverted U-shaped relationship between financial depth and output growth. When firms do not search enough for new technologies, increasing the relative amount of loans results in higher innovation and

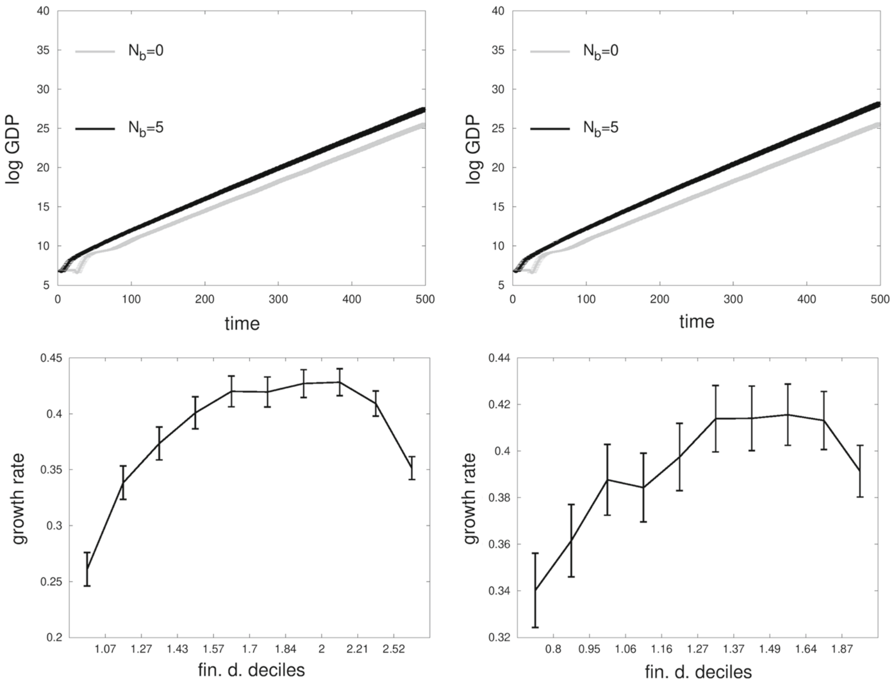

Fig. 14 Role of information in banking activity. Left: asymmetric information (baseline). Right: perfect information, banks serve imitators first and interest rates are differentiated (0.07 for imitators and 0.12 for explorers). Top: MC average of log GDP with a banking sector ($N_{\mathrm{b}} = 5$) and without ($N_{\mathrm{b}} = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\mathrm{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

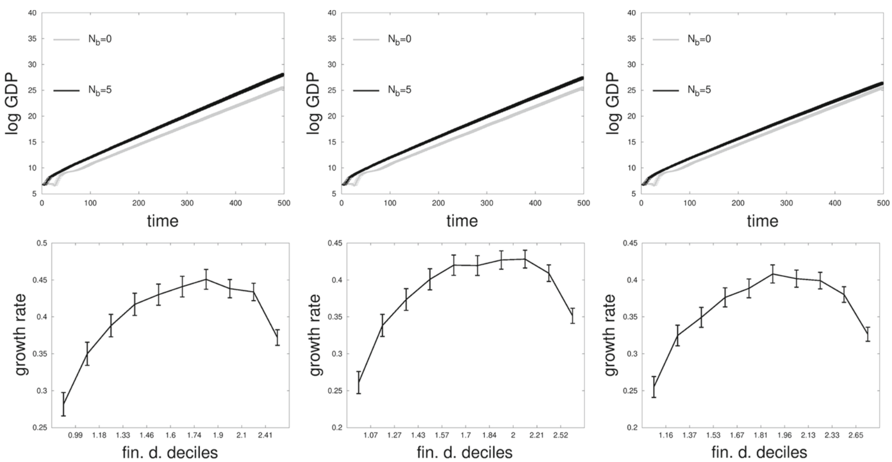

Fig. 15 Share of savings invested in banks' equity. Left: $\gamma_1 = 0.005$. Mid: $\gamma_1 = 0.01$ (baseline). Right: $\gamma_1 = 0.02$. Top: MC average of log GDP with a banking sector ($N_{\mathrm{b}} = 5$) and without ($N_{\mathrm{b}} = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\mathrm{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

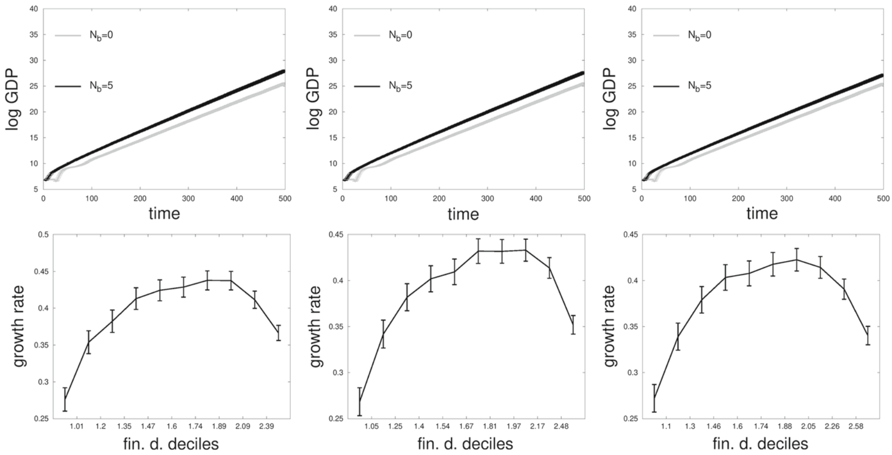

Fig. 16 Share of savings devoted to create a new bank. Left: $\gamma_2 = 0.2$. Mid: $\gamma_2 = 0.4$. Right: $\gamma_2 = 0.6$. Top: MC average of log GDP with a banking sector ($N_\mathrm{b} = 5$) and without ($N_\mathrm{b} = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\mathrm{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

faster technological diffusion, thus spurring GDP growth. However, excessive levels of credit sustain the animal spirits of firm engaged in unfruitful exploration undermining production and savings.

Overall, this suggests that the interaction between innovation and finance may play a more fundamental role in fueling growth than previously thought.

The current model relies on a set of simplifying assumptions which we made to let the analysis be focused on the interplay between credit and growth characterized by the exploration–exploitation trade-off. Hence, the model could be extended in several ways. First of all, the credit mechanism can be refined letting agents and banks decide in a more sophisticated way how to demand or supply credit. One could endogenize the formation of links between banks and firms. In the basic version of the model, we exogenously select bank–firm links once and for all before simulations start. Instead, one could allow banks to differentiate interest rate depending on the applicant and the observable information, while firms should be allowed to hold multiple credit lines or to strategically switch among different banks depending on proposed interest rates. Moreover, the willingness to require credit should be inversely related to the interest rate level and the possibility of financing production should be introduced. Then, an interbank lending market could be introduced in order to allow banks to extend loans to one another for a number of time steps. Finally, on the policy side, one could study the impact of more sophisticated macro- and micro-prudential regulations as well as the role of patient finance, introducing, e.g., a public investment bank.

Compliance with ethical standards

Conflict of interest All authors declare that they have no conflict of interest.

A Additional analyses

In Appendix, we collect some additional analyses we made to check the robustness of our results.

First we investigate what happens when more "risk averse" explorers are considered. To do that, we assume that the amount of resources necessary to start an exploration is

$$(1+\theta)\,\frac{C_{i,t}}{\pi} \geq E_i^{\text{ex}},$$

with $\theta \geq 0$ representing a safety buffer. That is, for precautionary motives an explorer requests more resources than those she expects to consume during the travel.

Figure 17 shows the results with different values of θ. As one can notice, no significant difference emerges from the introduction of such safety mechanisms. This is due to the fact that the positive effect of lowering the risk of bankruptcy is counterbalanced by the negative effect of committing more resources to fewer explorations. This is confirmed by the expansion of financial depth. Indeed, banks end up financing less (but larger) projects; thus, when an innovative project fails, it has more severe consequences on the economy.

Next, we consider the case in which production is possible also during imitation and exploration. To do that, we assume that in each period of sailing an agent is able to generate the amount of GDP she was producing during her last period as miner on the island she left. Figure 18 shows the comparison between our baseline setting and this new scenario. As expected production during navigation has a positive effect on growth, which becomes even more evident when a banking sector is present. Indeed, in this setting the imitation and exploration boosting provided by credit does not correspond anymore to a lack of accumulation. The relation between financial

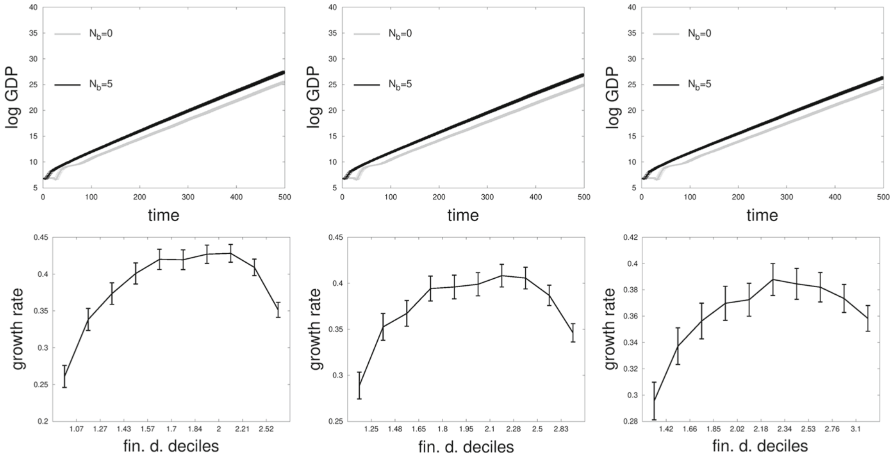

Fig. 17 Safety buffer for exploration. Left: $\theta = 0$ (baseline). Mid: $\theta = 0.1$. Right: $\theta = 0.2$. Top: MC average of log GDP with a banking sector ($N_b = 5$) and without ($N_b = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\text{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

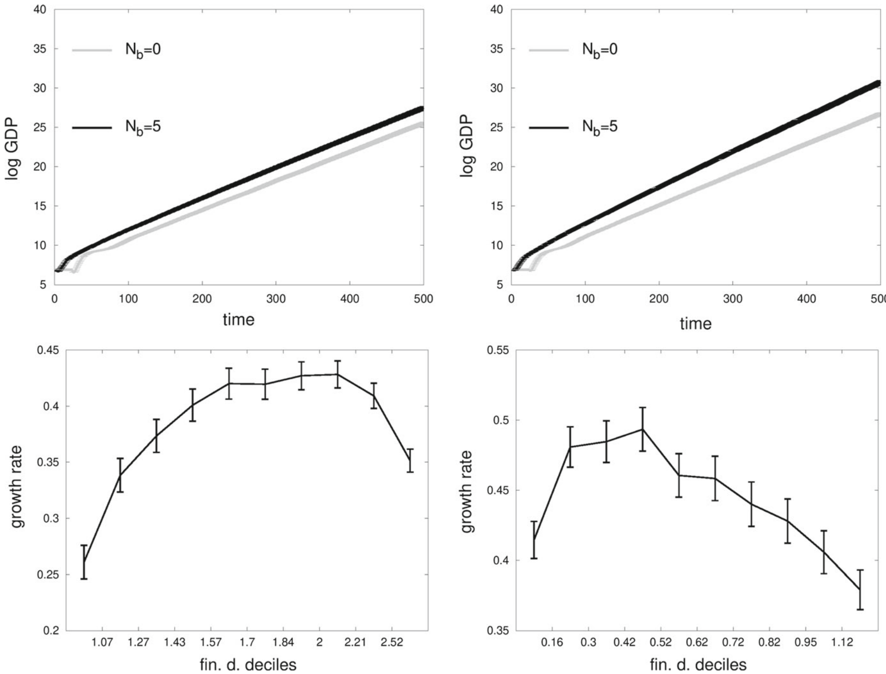

Fig. 18 Production during imitation or exploration. Left: no production (baseline). Right: production during sailing equal to last production. Top: MC average of log GDP with a banking sector ($N_{\mathrm{b}} = 5$) and without ($N_{\mathrm{b}} = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\mathrm{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

depth and growth is still inverted U shaped, and it is interesting to notice how the financial sectors shrink. Moreover, an expansion of finance produces a negative effect on growth relatively earlier. These are the consequences of larger accumulation of resources, which dynamically increases the risk of over-exploration.

In the previous setting, however, production during navigation implies that exploration and imitation activities are basically costless. In the baseline setting, instead, moving in the technological space entails two costs. Indeed, foregone production (an opportunity cost) should be added to the explicit cost of foregone consumption described in Sects. 3.3 and 3.4. Hence, we explore now some intermediate cases. Figure 19 compares the results obtained under the baseline setting with those one gets when firms are allowed to generate a share of their last production as miners to finance explicit exploration and imitation costs. More specifically, we assume that production during sailing finances half of the explicit navigation cost and we investigate what happens when such cost increases by 50% (mid panels) or remains as in the baseline (right panels). Thus, in the first case the total cost of sailing decreases by 25% of the baseline explicit cost in terms of foregone consumption, while in the second case the total cost decreases by 50% of the baseline explicit cost. As one can notice, our results are overall robust to these different specifications. Since in both cases the total cost is significantly reduced, exploration and imitation become cheaper than in the

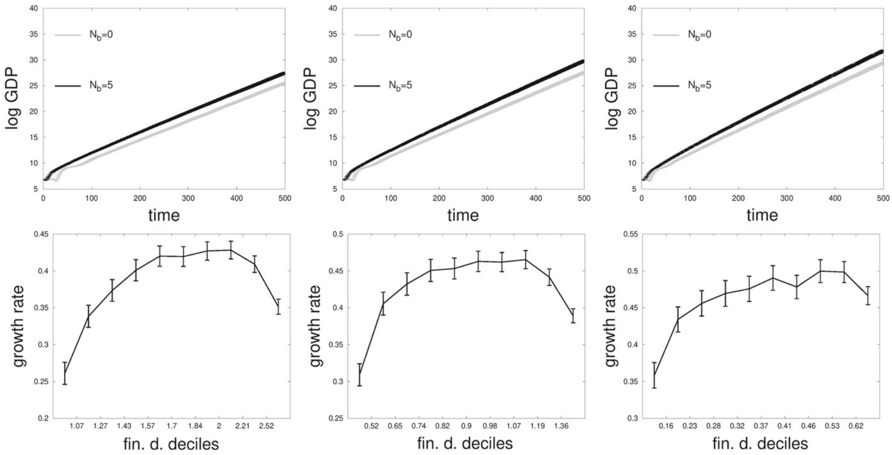

Fig. 19 Production during sailing and cost of exploration and imitation. Left: baseline. Mid: production covers half of the explicit navigation cost which increases by 50%. Right: production covers half of the baseline explicit navigation cost. Top: MC average of log GDP with a banking sector ($N_\mathrm{b} = 5$) and without ($N_\mathrm{b} = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\mathrm{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

baseline and this has a positive effect on long-run growth. Moreover, in those cases firms need to borrow less resources and the financial sector shrinks. Thus, the negative effect of a large financial sector is reduced and the risk of observing credit fueled over-exploration decreases.

Now we explore how our results change when the strength of cumulativeness in technical change weakens. As in the original FDM, cumulativeness plays an important role since it is at the core of the dynamic increasing returns process that drives self-sustained exponential growth. Indeed, as one can notice in Fig. 20, with lower values of ϕ growth declines and such reduction is more evident when a financial sector is active. This follows from the fact that, in this scenario, discovering a new technology is less rewarding and agents take more time to pay back their loans. The inverted U-shaped relation between finance and growth is robust to lower values of ϕ, even if the negative effect of large financial depth seems to weaken. This is because larger exploration is needed when new technologies are only marginally more productive than old ones; thus, over-exploration becomes less likely.

Then, we analyze how our results change when imitators move faster in the technological space. Thus, adopting an already existing technology, as well as having the relevant advantages of being deterministic and moving through the shortest path, has also the advantage of a reduced time for implementation and hence a lower cost. As one can notice in Fig. 21, favoring imitation implies higher growth and such effect becomes even stronger when a financial sector is active. This follows from a mitigation of the incidence of over-exploration: faster and cheaper adoption implies that, on average, firms devote more resources to imitation than to exploration, equilibrating the trade-off. This is confirmed by the form of the inverted U-shaped relation between financial depth and growth, whose maximum shifts to the right.

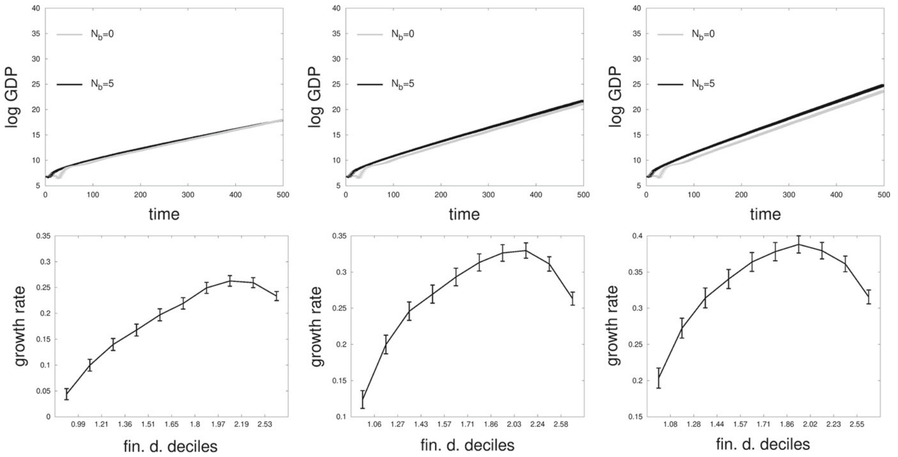

Fig. 20 Strength of cumulative learning effect. Left: $\phi = 0.2$. Mid: $\phi = 0.3$. Right: $\phi = 0.4$. Top: MC average of log GDP with a banking sector ($N_\mathrm{b} = 5$) and without ($N_\mathrm{b} = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\mathrm{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

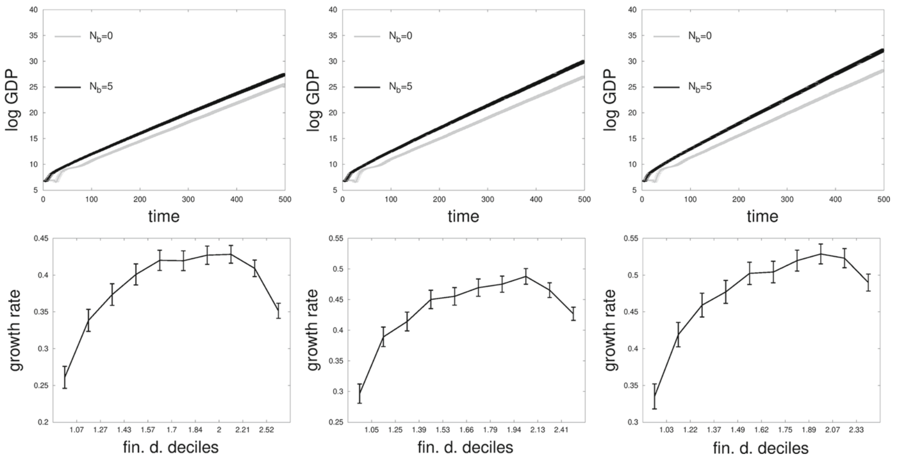

Fig. 21 Speed of imitators. Left: 1 step per period (baseline). Mid: 1.5 steps per period. Right: 2 steps per period. Top: MC average of log GDP with a banking sector ($N_\mathrm{b} = 5$) and without ($N_\mathrm{b} = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\mathrm{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

In the end, we complement the analyses in Figs. 11 and 12 observing how our results vary when large values of minimum capital requirement are considered. As one can notice in Fig. 22, when χ increases too much growth is negatively affected. This is because, when banks have to restrain credit because of a large capital requirement, the economy suffers of a lack of imitation and exploration, especially in the first phases of development. This is also confirmed by the fact that the relation between financial

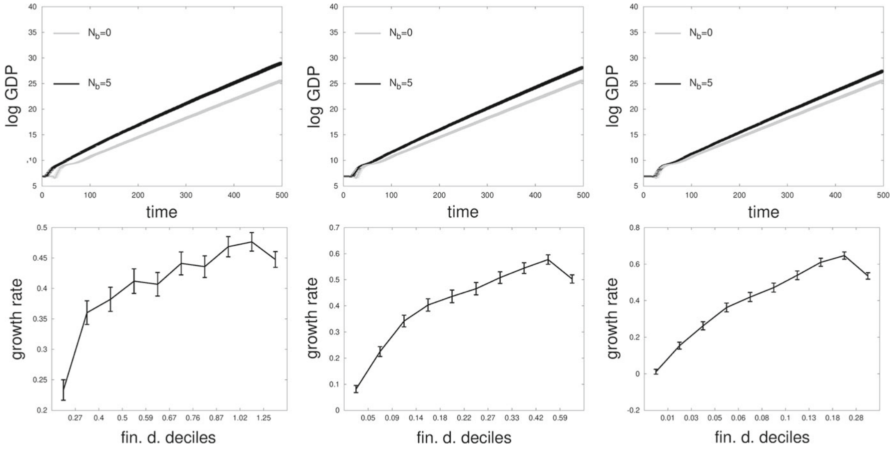

Fig. 22 Minimum capital requirement. Left: $\chi = 0.5$. Mid: $\chi = 2$. Right: $\chi = 5$. Top: MC average of log GDP with a banking sector ($N_\mathrm{b} = 5$) and without ($N_\mathrm{b} = 0$). Bottom: MC average of G_t^{10} for the different subsamples generated by the deciles of $\overline{\mathrm{FD}}_{t-10}^{10}$. Confidence bands are set as three standard errors away from Monte Carlo sample averages

depth and growth becomes increasingly positive and steep, while over-exploration is a very rare event.

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