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Abstract

In this paper we replicate most of the stylized facts characterizing the decline in business dynamism in the USA highlighted by Akcigit and Ates (2021) and provide an explanation of their emergence by means of a macroeconomic agent-based model populated by two types of firms: innovators who generate new and more productive capital goods, and entrepreneurs who employ labor and capital goods to produce consumption goods. A key ingredient of the model is the assumption that the entrepreneurs' access to new and better capital goods depends on the knowledge gap, i.e., the wedge between the firm's technical knowledge and the state of technology embodied in new capital goods. Within this framework, we investigate the obstacles to knowledge diffusion subsequently leading to declining business dynamism. Our findings indicate that only when knowledge diffusion decreases in both the technology imitation and adoption processes does it lead to high market concentration and markups, falling labor share and productivity growth. Patents are an important obstacle to knowledge diffusion. We find an inverse U-shaped relationship between patent strength and growth: moderate levels of patent protection can stimulate growth, but strong protection leads to rising market power and slower growth.

JEL-Codes: O310, O320, O330, O340.

Keywords: innovation, imitation, knowledge diffusion, knowledge gap, patents.

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1 Introduction

In Friedrich Hayek's pre-analytic vision, the diffusion of knowledge plays a key role in economic decision making. In his influential article "The use of knowledge in society" (1945), he argued that knowledge is dispersed among countless individuals and can be effectively aggregated and transmitted only in competitive markets through the price mechanism, resulting in a "spontaneous order" characterized by the efficient allocation of resources.[1] Any attempt to centralize decision making would prove detrimental, as a central planning authority does not possess the knowledge required to make optimal economic decisions. Accordingly, he strongly advocated the superiority of decentralized markets over central planning.

Hayek's view of dispersed knowledge in market economies rests upon three essential premises: (1) it is practically impossible for any individual or planning committee to possess comprehensive knowledge; (2) private economic subjects are self-interested and acquisitive and respond to signals consistently; (3) markets are competitive.[2] While the first two assumptions are broadly in line with reality, the validity of the third assumption has come under scrutiny in the light of the growing market concentration observed in contemporary economies in the past four decades. The empirical literature has emphasized the connection between the increase in market concentration and several stylized facts related to the decline in business dynamism (relative to the pre-1980 period), including higher markups, falling labor share, slower capital accumulation and productivity growth, widening productivity gap between industry leaders and laggards, as well as a shrinking flow of new entrants and lower dispersion in firm growth rates (Decker et al., 2016; Syverson, 2019; Calvino et al., 2020; De Loecker et al., 2020; Akcigit and Ates, 2021).

In order to explore the mechanisms driving the observed trends, Akcigit and Ates (2023) employ an endogenous growth model augmented with firm dynamics to show that *a reduction in knowledge diffusion* accounts for the majority of stylized facts of declining business dynamism. This is a key insight corroborated by recent empirical evidence. In the last four decades, in fact, technological knowledge has been increasingly concentrated in a handful of very innovative firms. These firms have benefited from sizable barriers to the spreading of this knowledge to the rest of the corporate sector, affecting both the development and adoption of advanced technologies. On the one hand, since the Bayh-Dole Act of 1980 there has been a considerable increase in US patent applications, many with a defensive intent, that have erected barriers to protect the top 1% of innovative firms, thus preventing the spillover of knowledge to other firms (Akcigit and Ates, 2021; Dosi et al., 2023b).[3] On the other,

[1] In his view, changes in market prices play the role of signals that allow individuals, who may otherwise lack knowledge, to update their beliefs about the state of the economy and make informed decisions.

[2] As Hayek put it in his 1944 book "The Road to Serfdom", "The price system will fulfill [its] ... function only if competition prevails, that is, if the individual producer has to adapt himself to price changes and cannot control them."

[3] More specifically, based on USPTO data, Akcigit and Ates (2021) show that since the mid-1980s there has been a steady surge in the share of reassigned patents held by the largest 1 percent of buyers of patents. Moreover, the share of applications for patents coming from the top 1 % of firms with the largest patent stocks has substantially

recent survey-based evidence reveals that only a small group of large and highly productive firms are adopting advanced digital technologies (Zolas et al., 2021; Acemoglu et al., 2022).[4] Moreover, a strong correlation emerges between the adoption of advanced digital technologies and the presence of complementary assets at the adopting firm, such as widespread digital capabilities and a robust digital infrastructure (Calvino and Fontanelli, 2023; Cirillo et al., 2023). These findings bring to the fore the crucial role that accumulated technological knowledge plays in facilitating the adoption and diffusion of cutting-edge technologies (Hötte, 2020; Brynjolfsson et al., 2021; Wang et al., 2021).[5]

In this paper we build on this evidence to explore the causes of declining business dynamism and its macroeconomic and industrial consequences by means of a macroeconomic agent-based model (ABM) centered upon knowledge accumulation. The present setting is an extended variant of the model developed by Terranova and Turco (2022), i.e., a macroeconomic ABM with capital and credit (along the lines of Assenza et al. (2015)) augmented with technical change and knowledge accumulation. By means of simulation experiments we explore the conditions under which a decline in knowledge diffusion at the micro level leads to an emergent dynamics of declining business dynamism at the aggregate level.

In our model technical change originates from capital good producers (*innovators*) who sell machine tools to producers of consumption goods (*entrepreneurs*). Technical progress, therefore, is embodied in capital goods. Entrepreneurs, however, do not have immediate and uniform access to innovation. They must accumulate sufficient technical knowledge to incorporate new and more productive machines into their production process. Entrepreneurs that lack sufficient knowledge have an incentive to stick to capital goods of lower quality. In other words, the availability of technical knowledge at the adopting firm acts as a knowledge constraint on technology adoption. This idea is incorporated in a key feature of the model, the *knowledge gap*, i.e., the difference between the technical advancement of the capital good and the technical knowledge accumulated by the firm. The wider the knowledge gap, the lower the incentive for the firm to access more advanced machines. We exploit the granularity and flexibility of the AB setting to study in depth

increased, going from 37% in 1980 to 50% in 2012. Further, using patent data on the US pharmaceutical industry, Dosi et al. (2023b) show that since the 1980s patenting has gone up exponentially, with an increasing relevance of defensive patents around existing compounds and therapies, as well as new applications of existing molecules and "me-too" drugs. At the same time, the rate of innovation has slowed down, as shown by the declining pattern of new patent families vis-a-vis the stock of existing ones, whereas patent family size has significantly increased, signalling rising patent thickets and higher barriers to imitation. Krieger et al. (2022) document similar patterns.

[4] According to Acemoglu et al. (2022, 2023), between 2016 and 2018 adoption rates of advanced technologies in the US were modest (3.2% for AI, 2% for robotics) and concentrated in large firms. Additionally, they document that adopters were already large and growing faster before advanced technologies became generally available. Calvino and Fontanelli (2023) present comparable findings for OECD countries.

[5] A few empirical papers document the importance of complementarities between the firms' technical know-how and their ability to employ technological innovations (Bresnahan et al., 2002). For instance, in the context of the Information and Communication Technologies (ICT) revolution, Doms et al. (1997); Mairesse et al. (2001); Brynjolfsson and Hitt (2000) show that firms are able to exploit gains from the introduction of new technologies when they have pre-existing organizational capabilities. Conversely, Dosi et al. (2010b) emphasize the negative effects of adopting ICT without corresponding changes in technical and organizational practices.

the effects of decreasing knowledge diffusion.

We first calibrate the baseline scenario to reproduce the macroeconomic behavior of the US economy until the 1980s. For obvious reasons, we characterize the baseline as the *high knowledge diffusion* scenario. Then, by modifying a set of knowledge-related parameters we construct an alternative *low knowledge diffusion* scenario to replicate the stylized facts of declining business dynamism in the last four decades. Simulation results show that in the case of low knowledge diffusion the economy exhibits a tendency towards increasing concentration driven by widening productivity gaps across firms, resulting in an increasing aggregate markup and declining labor share and GDP growth. If imitation is weak and knowledge constraints are binding, in fact, technological differences among capital goods will translate into a wider productivity gap between "knowledge intensive" entrepreneurs (*leaders*) and entrepreneurs with low accumulated knowledge (*laggards*) because only the former are able to adopt better techniques, thus gaining a competitive advantage over the latter. Consequently, as their market shares increase, the leaders use their enhanced market power to charge higher markups, generating a shift of income distribution from wages to profit, with negative effects on demand and growth. Sensitivity analysis leads to the following findings: (i) a higher knowledge polarization in technology adoption fosters GDP growth by allowing the best techniques to become dominant only if the knowledge constraints are not too binding, otherwise it leads to greater concentration and market power; (ii) the decline in business dynamism emerges only if a reduction in knowledge diffusion affects both imitation among innovators and technology adoption among entrepreneurs. Our framework thus provides a more sophisticated and nuanced interpretation of the fundamental drivers behind the phenomenon under investigation.

Finally, to provide a more concrete interpretation of the decline in knowledge diffusion, we introduce the possibility for capital good producers to *patent* their innovations and analyze the effects of different patent regimes on competition and growth. A patent regime is characterized by a certain *length*, i.e., duration of the patent, and *breadth*, i.e., dimension of the protected area. We model patents so as to capture the different effects on firms' behavior documented in the literature: (i) *protection effect*, that inhibits imitation and blocks innovations falling within the protected area; (ii) *disclosure effect* that makes it easy to imitate innovations whose patents have expired; (iii) *incentive to patent effect*, by which the best technologies in the eyes of innovators are more likely to be patented; (iv) *patent incentive to innovate effect* that induces patenting firms to increase their innovative effort when patenting is deemed more profitable.

We find that patents have ambiguous effects on growth, depending on the strength of the patent regime and the type of transmission channels under consideration. When the length and breadth of patents are low (i.e., the patent regime is "weak"), an increase in patent protection has a positive influence on GDP, especially when the best innovations are more likely to be patented (incentive to patent effect) and patenting firms are motivated to increase their innovation effort (patent incentive to innovate effect). However, when patent protection becomes overly strict, the economy experiences greater concentration and output growth declines.

The paper is organized as follows. After a concise review of the literature (section 2), we present the building blocks of the model in section 3. Section 4 presents the findings obtained through simulations in the absence of patents. We introduce patents and discuss their effects in section 5. Section 6 concludes.

2 Related literature

This paper contributes to several strands of literature. Firstly, it adds to the ongoing debate on declining business dynamism (Decker et al., 2016; Calvino and Criscuolo, 2019; Calvino et al., 2020; Akcigit and Ates, 2021). This literature offers a comprehensive overview of several long-term trends observed in advanced economies since the 1980's: rising market concentration (Grullon et al., 2019; Autor et al., 2020), rising markups (De Loecker et al., 2020), falling labor share (Autor et al., 2017; Barkai, 2020), slower capital accumulation and productivity growth (Gutiérrez and Philippon, 2017), declining flows of new entrants and job re-allocation (Andrews et al., 2015; Decker et al., 2016),[6] widening productivity gap between industry leaders and laggards, lower dispersion in firm growth rates (Decker et al., 2016; Calvino et al., 2020). In order to jointly explain these facts, Akcigit and Ates (2021, 2023) propose an endogenous growth model augmented with firm dynamics and show that a decline in knowledge diffusion can explain most of these stylized facts.[7] While analytically rigorous and formally elegant, the general equilibrium model they propose is grounded on rather restrictive assumptions and an overly simplified characterization of the knowledge diffusion process, captured by one single parameter.

We build on this insight but in a different setting, exploiting the granularity and flexibility of the agent-based approach to represent a detailed process of knowledge generation and diffusion, grounded on the distinction between producers of new technology (innovators) and adopters (entrepreneurs). We contribute, therefore, also to the growing body of literature on agent-based macroeconomics (Delli Gatti et al., 2011, 2018; Dawid and Delli Gatti, 2018; Dosi and Roventini, 2019), with a special focus on technical change, growth and inequality (Dawid, 2006; Russo et al., 2007; Dawid et al., 2018; Caiani et al., 2019; Dosi et al., 2021; Bertani et al., 2021; Fanti,

[6] Focusing on the dynamics of entry-exit and job reallocation rates across 18 countries and 22 industries over the last two decades, Calvino et al. (2020) conclude that the decline in business dynamism in OECD originates mainly from developments occurring at the industry level, within specific 2-digit sectors, rather than from re-allocations across sectors. There is significant heterogeneity, however, in the magnitude and speed of this decline across countries and sectors. Telecommunications, IT, Scientific R&D and Media have experienced the sharpest decline, while Food and Beverage and Textile have been less affected by this phenomenon.

[7] In Akcigit and Ates (2023), two effects are at play: (i) the *discouragement effect* on the laggards, and (ii) the *escape competition effect* on the leaders. The first effect captures the weakening of the laggards' incentive to catch up in the more protected environment of the last four decades. The second effect describes the weakening of the leaders' incentive to innovate to defeat competitors. These effects jointly determine a wider productivity gap between leaders and laggards, strengthen the market power of the former and lead to higher markups and profit share.

2021; Fierro et al., 2022; Terranova and Turco, 2022). In particular, our paper closely aligns with research that emphasizes the importance of complementary skills and accumulated knowledge in driving technology adoption and industrial dynamics (Dawid et al., 2019; Hötte, 2020; Dosi et al., 2022).

To the best of our knowledge, no previous work in the ABM field has attempted to jointly explain the stylized facts of declining business dynamism. However, Mellacher (2021) and Dawid and Hepp (2022) have pursued analogous objectives, investigating the impact of distinct technological regimes on growth, market concentration and inequality, albeit by means of different modelling approaches.

Lastly, by introducing a patent system and examining its broader macroeconomic implications, we contribute to the literature on the impact of intellectual property rights (IPR) on innovation and growth. In spite of a substantial body of theoretical and empirical literature dating back at least to Taylor and Silberston (1973) that addresses the effects of patent protection, the empirical findings in this domain are mixed (Cohen, 2010). More recently, Dosi et al. (2023c) have developed an evolutionary agent-based model of the US pharmaceutical sector to explore the impact of different configurations of the patent system upon innovation and competition. Their study reveals predominantly adverse effects stemming from a strong patent system, suggesting that optimal patent length and scope, if anything, should be set to the minimum levels.

In a parallel vein, in this paper we incorporate the patent regime within a macroeconomic framework, emphasizing two incentive channels (the *incentive to patent* effect and the *patent incentive* to innovate effect). Our analysis unveils more nuanced outcomes, somewhat in line with Acemoglu and Akcigit (2012). Specifically, for low values of patent duration and breadth, patent protection could indeed foster innovation and growth when both incentive channels – i.e., incentive to patent and patent incentive to innovate – are concurrently operational. However, like Dosi et al. (2023c), our findings underscore that an excessively stringent patent system is detrimental to GDP growth. More generally, by investigating the knowledge diffusion process and the patent protection policies, our study also contributes to the (ABM) literature studying alternative innovation policies and their potential effects on the economy's performance in both the short and long-term (Dosi et al., 2023a).

3 Model setup

3.1 Agents and markets

The setup we propose in this paper builds upon the macro agent-based model with capital and credit developed by Assenza et al. (2015) (ADG hereafter), then augmented with technical change and knowledge accumulation by Terranova and Turco (2022) (TT hereafter). Agents are grouped in sectors. The corporate sector consists of F_k producers of capital goods or "machine tools" (K-goods for short) and F_c producers of consumption goods (C-goods). Producers of C-goods will be referred to as C-firms. Analogously producers of K-goods will be referred to as K-firms. C-firms purchase capital goods from K-firms and sell their output to households.

The TT model introduces technical progress into ADG following the evolutionary approach pioneered by Dosi et al. (2010a). K-firms are at the origin of technical progress as they generate innovations that are embodied in new and better capital goods. For this reason, K-firms will play the role of *innovators*. Each K-firm, therefore, can produce different vintages of capital goods of the same brand. On the other hand, C-firms introduce technical progress into their production process through the purchase of new machine tools. For this reason they are the *entrepreneurs*.

The household sector consists of W workers and $F = F_c + F_k$ firm owners or "capitalists" (one owner per firm). Households receive income (wages, unemployment benefits and dividends), spend in consumption goods and save in the form of deposits. Workers can be of two types: *production workers* are employed in the production of goods while *research workers* carry out R&D. For simplicity, the banking sector consists of only one bank, that collects deposits from households, extends loans to firms and buys Government bonds. The public sector taxes wages and dividends and provides unemployment subsidies. Deficits are financed by issuing bonds absorbed by the bank.

In line with TT, quantity and price decisions of C-firms are taken separately, the former based on expected sales and the latter on market power captured by the change in market share. In ADG "capital" is a homogeneous input; in TT capital goods are heterogeneous in terms of productivity, whose improvements depend upon a stochastic innovation/imitation process. K-firms perform R&D in order to generate new and better machine tools. C-firms perform R&D in order to accumulate *technological knowledge*, which enhances their ability to identify and employ new and better machine tools.

Contrary to TT, we have introduced a few major changes to the model setup coherent with the focus of the present paper: (i) we have expanded the K-sector, departing from the assumption of infinitely elastic supply and employing a production function approach akin to the C-sector (see section 3.8); (ii) given its marginal role, we have streamlined the representation of the banking sector (see section 3.10); (iii) we have introduced a patent system to enable K-firms to safeguard their innovations against imitation (see section 5). Furthermore, the model has been entirely re-calibrated to quantitatively and qualitatively match the stylized facts related to the declining business dynamism (see validation section 4.1).

As for the market protocols, workers and firms interact in decentralized labor, credit, consumption, and capital goods markets in line with Assenza et al. (2015). The interaction occurs via the search-and-matching mechanism (Riccetti et al., 2015). The choice of the capital vintage is determined by a logit model, similarly to Dawid et al. (2019). Each C-firm chooses from the same set of machines, but the probability of picking a given vintage crucially depends on the firm's ability to exploit the innovations embodied in that vintage, that in turn depends on the firm's knowledge gap.

This assumption allows to investigate more in-depth the role of C-firms' accumulated knowledge in the process of acquisition of heterogeneous capital goods.

3.2 Sequence of events

Over one period of the simulation run, events unfold in the following order:

1. *Planned production and input demand:* On the basis of expected sales, firms decide desired production and labor demand for production workers and research workers. C-firms choose the utilization rate of the capital stock.

2. *Choice of supplier of K-goods:* C-firms select their potential supplier of capital goods on the basis of the price and the effective productivity of the machine tools. The effective productivity is firm-specific as it depends on the knowledge gap of the purchasing C-firm.

3. *Credit market:* If planned production costs exceed internal funds, C-firms resort to the bank asking for a loan.

4. *Labor market:* Firms hire and fire production and research workers on the basis of their labor requirements; employees receive a wage, net of taxes. The unemployed receive an unemployment subsidy.

5. *Actual production and price:* Firms set production as the minimum between desired (or planned) and potential output, i.e., output that can be produced on the basis of the availability of inputs. The firm, in fact, may be unable to achieve the desired scale of production if inputs and/or funding are insufficient. The price is determined by charging a markup over the unit labor cost.

6. *Capital goods market:* C-firms willing to expand their capital stock buy machine tools from the selected supplier. Purchased capital goods are available for the production process of C-firms starting from the next period.

7. *R&D expenditure:* Both C- and K-firms carry out R&D activity using profits realized in the previous period. C-firms update their knowledge stock; K-firms perform innovation and imitation activities to develop more efficient vintages of capital goods.

8. *Consumption goods market:* Having defined their consumption budget, households visit a given number of firms and choose the supplier after comparing their selling prices.

9. *Firms' profits, dividends and net worth:* Firms collect revenues and compute profits. They distribute part of their profits to capitalists as dividends and allocate part of their profits to the R&D budget that will be invested in the following period. Retained earnings drive the accumulation of net worth.

10. *Taxes and subsidies:* The government collects taxes on wages and dividends and distributes unemployment benefits to unemployed workers.

11. *Entry-exit dynamics:* If equity turns negative or liquidity is not sufficient to repay principal and interest, the firm defaults. Each bankrupt firm is replaced by a new entrant, endowed with initial equity provided by the owner of the corresponding bankrupt firm.

12. *Public sector deficit and bond issuance:* To finance outlays in excess of tax revenues, the Government issues bonds, purchased by the bank. Public debt is updated accordingly.

13. *Bank's profits, dividends and net worth:* The bank collects interest payments, records non-performing loans and computes profits. The bank distributes part of the profits to the bank's owners as dividends. Retained earnings drive the accumulation of net worth. If the latter turns negative, all households participate in the bail-in proportionally to their deposits.

3.3 C-firms

C-firms, indexed with $i = 1, 2, ...F_c$, demand labour, machine tools and credit, and supply C-goods to households.

Planned production The firm sets the desired scale of production $\tilde{Y}_{it}$ on the basis of expected sales Q^e_{it}. In each period t, for the i-th firm, the following identity holds:

$$\tilde{Y}_{it} + inv_{it-1} = Q^e_{it} + inv^*_{it} \tag{1}$$

where inv_{it-1} are inventories of unsold goods carried out from the past[8] and inv^*_{it} are desired inventories.[9] The latter, in turn, are equal to a fraction $\iota \in (0, 1)$ of expected sales: $inv^*_{it} = \iota Q^e_{it}$. Hence planned output is

$$\tilde{Y}_{it} = Q^e_{it}(1 + \iota) - inv_{it-1}. \tag{2}$$

By assumption, firms are unable to observe actual demand, hence they compute expected sales, Q^e_{it}, by means of a simple adaptive rule based on past forecasting errors with updating coefficient $\rho \in (0, 1)$. In symbols:

$$Q^e_{it} = Q^e_{it-1} + \rho(Q_{it-1} - Q^e_{it-1}) \tag{3}$$

[8] We assume that inventories of unsold goods are storable but they deteriorate at a rate δ^{inv} per period. Hence $inv_{it} = inv_{it-1}(1 - \delta^{inv})$

[9] The firm holds desired inventories to smooth production in the presence of short-term demand swings (Caiani et al., 2020).

where Q_{it-1} represents actual sales. Expected sales in period t, therefore, turn out to be a weighted average of past sales, with exponentially decaying weights:

$$Q^e_{i,t} = \rho \sum_{s=0}^{\infty} (1-\rho)^s Q_{i,t-1-s}. \tag{4}$$

Also planned output, therefore, is anchored to past sales:

$$\tilde{Y}_{it} = (1+\iota)\rho \sum_{s=0}^{\infty} (1-\rho)^s Q_{i,t-1-s} - inv_{it-1}. \tag{5}$$

In order to produce, the firm combines labor N_{it} and the capital stock, consisting of a bundle of heterogeneous capital goods – i.e., machine tools of different "vintages". Therefore, the production function of the i-th firm is:

$$Y_{it} = \min\left(\sum_{v \in V_{it}} \omega^v_{it} k^v_{it} A^v_{it}, B_{it} N_{it}\right) \tag{6}$$

where Y_{it} is output generated by the available factors of production, k^v_{it} represents units of capital (machine tools for short) of vintage v in the capital stock of firm i, V_{it} is the set of vintages of machine tools owned by firm i, A^v_{it} is the *actual* productivity of the machine tools of vintage v installed at firm i, ω^v_{it} is the utilization rate of these machine tools, B_{it} is the productivity of labour. In our setting vintage is associated to "quality" measured by the productivity of the machine tool: new vintages are characterized by higher productivity. The cardinality of the set of vintages is time varying because each K-firm is in principle producing more than one vintage of machine tools by innovating/imitating (more on this in section 3.8). The actual productivity of a machine tool of a given vintage installed at firm i, A^v_{it}, may be lower than its potential productivity A^v. The firm will be able to exploit the machine tool fully ($A^v_{it} = A^v$) only if it has accumulated "sufficient" technical knowledge (more on this in section 3.4).

Assuming that labour is abundant we can write

$$Y_{it} = \sum_{v \in V_{it}} \omega^v_{it} k^v_{it} A^v_{it} = A_{it} K_{it}. \tag{7}$$

Output is the sum of the number of machine tools of each vintage (weighted by capacity utilization) multiplied by the corresponding productivity. By simple algebraic manipulation we can interpret this sum as the product of the "capital stock" $K_{it} = \sum_{v \in V_{it}} \omega^v_{it} k^v_{it}$ times the "average productivity of capital" $A_{it} := \sum_{v \in V_{it}} x^v_{it} A^v_{it}$ where $x^v_{it} := \frac{\omega^v_{it} k^v_{it}}{K_{it}}$ is the weight of the machine tools of vintage v in the capital stock. Hence the production function can be written as follows:

$$Y_{it} = \min\left(A_{it} K_{it}, B_{it} N_{it}\right) \tag{8}$$

From perfect input complementarity follows that the capital-labour ratio (or capital intensity) is $K_{i,t}/N_{i,t} = B_{i,t}/A_{i,t}$. We assume that the capital-labour ratio – denoted with κ – is constant (so that technical change is Hicks-neutral) and uniform across firms (for simplicity).[10] Hence the productivity of labour at firm i is:

$$B_{it} = \kappa A_{it}. \tag{9}$$

This assumption has important implications. The adoption by firm i of new and more productive technologies incorporated in new vintages of machine tools reverberates on the average productivity of capital at the same firm and therefore on the productivity of labour, that will increase at the same rate.

To achieve planned production – defined in (5) –, in the short run the firm adjusts the rate of capacity utilization of the machine tools already installed, as well as employment. The capital stock changes through investment to satisfy long-run production requirements, in line with Assenza et al. (2015) (see section 3.5). Notice that actual output will be smaller than planned output if there is shortage of physical capital or lack of funding (compare steps 1 and 5 in the sequence of events).

Capacity utilization Having set the desired scale of activity, the firm begins production using the machine tools with the highest built-in productivity (the best vintage). If full utilization of these machine tools is not sufficient, the firm activates machine tools of the second most productive vintage and so on. At a certain stage of this procedure there will be a vintage of machine tools (the marginal vintage) such that full utilization would bring production beyond the planned level and no utilization would keep production below the planned level. The utilization rate of machine tools of the marginal vintage, therefore, will be set at the level that is necessary to achieve the desired scale of production.[11] The desired utilization rate of capital vintage v by firm i is therefore determined according to the following algorithm:

$$\omega_{it}^{v} = \begin{cases} 1 & \text{if} \quad \sum_{s=1}^{v-1} k_{it}^{s} A_{it}^{s} + k_{it}^{v} A_{it}^{v} \leq \tilde{Y}_{it} \\ \frac{\tilde{Y}_{it} - \sum_{s=1}^{v-1} k_{it}^{s} A_{it}^{s}}{k_{it}^{v} A_{it}^{v}} & \text{if} \quad \sum_{s=1}^{v-1} k_{it}^{s} A_{it}^{s} \leq \tilde{Y}_{it} \text{ and } \sum_{s=1}^{v-1} k_{it}^{s} A_{it}^{s} + k_{it}^{v} A_{it}^{v} > \tilde{Y}_{it} \\ 0 & \text{if} \quad \sum_{s=1}^{v-1} \omega_{it}^{s} k_{it}^{s} A_{it}^{s} \geq \tilde{Y}_{it}. \end{cases}$$

Employment C-firms need workers to carry out both production and R&D activities. We assume that funds devoted to research and development, denoted with RD_{it}, are used to hire research workers. Given the wage rate w_t, therefore, the firm post vacancies $N_{it}^{R} = \frac{RD_{it}}{w_t}$ (provided this ratio is at least equal to 1 unit of labour).[12]

[10] In order to guarantee that capital intensity does not change over time, we implicitly assume that the productivity of labour increases at the same rate as the average productivity of capital for any firm.

[11] See Caiani et al. (2020).

[12] For computational simplicity we assume that the labour contracts of research workers last one period only. In each period, therefore, the firm posts vacancies to recruit this type of workers. Moreover we assume that wages

As to production workers, given the desired rates of capacity utilization, from the assumption that the capital-labor ratio κ is constant follows that labour requirements are:

$$\tilde{N}_{it} = \frac{1}{\kappa} \sum_{v \in V_{it}} \omega_{it}^{v} k_{it}^{v}. \tag{10}$$

If desired employment $\tilde{N}_{it}$ is greater than the current workforce N_{it-1}, the firm post vacancies. Total vacancies posted by the i-th firm on the job market therefore are

$$J_{it} = \max(\tilde{N}_{it} - N_{it-1}, 0) + \mathbb{1}_R \frac{RD_{it}}{w_t} \tag{11}$$

where $\mathbb{1}_R$ is an indicator function that takes value 1 if $\frac{RD_{it}}{w_t} > 1$, zero otherwise.

The market protocol for the job market is characterized by search and matching as in Assenza et al. (2015): unemployed workers visit Z_u randomly sampled firms and get hired at the prevailing wage when a match occurs with a firm with unoccupied job vacancies. Therefore firms can reach the desired level of employment only if they are visited by a sufficient number of unemployed workers. It follows that, despite the absence of hiring or firing costs, job vacancies at some firms may remain unoccupied and at the same time some unemployed workers may not find a job. In case the current number of employees exceeds labor requirements, i.e., $\tilde{N}_{it} < N_{it-1}$, workers in excess are randomly selected from the firm's workforce and fired.

3.4 R&D, technological knowledge and the choice of the vintage

To install the machine tools produced by innovators, entrepreneurs must accumulate *technological knowledge*, that will be denoted with z_{it}. Technological knowledge is the firm's know-how, that is the set of skills and abilities accumulated over time within the firm. It comes from two sources. First, it can be built in-house by spending financial resources in R&D (Dosi and Nelson, 2010). We will denote with RD_{it} the research budget. Second, it can come from the knowledge accumulated by the other entrepreneurs through *knowledge spillovers*, z_{st}. The law of motion of the i-th entrepreneur's knowledge therefore can be written as follows:

$$z_{it} = (1 - \delta^z) z_{it-1} + RD_{it} + a_{it} z_{st} \tag{12}$$

where δ^z is the rate of obsolescence of knowledge and a_{it} is the sensitivity of the firm's technological knowledge to knowledge spillovers (of which we will provide an interesting interpretation momentarily). Let's dig deeper into each of these two sources in turn.

The firm devotes to (in-house) R&D a constant fraction σ of past retained profits π_{it-1}^{r}: $RD_{it} =$

are uniform across types of workers: production and research workers earn the same salary. These simplifying assumptions can be easily relaxed.

$\sigma\pi^r_{it-1}$. These resources are spent to pay for the wages of research workers ($RD_{it} = w_t N^R_{it}$) who contribute to the *internal accumulation* of technological knowledge. Knowledge, however, is partly a public good: the i-th entrepreneur can benefit from the *knowledge spillover* coming from the other C-firms. We assume that the knowledge spillover z_{st} is increasing with the new technological knowledge of the competitors, that in turn is affected by their R&D spending: $z_{st} = \psi \sum_{s \neq i} RD_{st}$ where ψ is the intensity of knowledge spillovers.

Following the seminal work by Cohen and Levinthal (1989) we assume that the role of RD_{it} is twofold: (i) it internally generates technical knowledge at firm i; (ii) it increases the i-th firm's *absorptive capacity*, i.e., its ability to assimilate knowledge spillovers. To capture the latter (ii) we define absorptive capacity as follows

$$a_{it} = 1 - e^{-\eta \overline{RD}_{it}}, \tag{13}$$

where $\eta > 0$. $\overline{RD}_{it}$ is the long run internal R&D effort, computed by means of the following adaptive algorithm

$$\overline{RD}_{it} = \xi \overline{RD}_{it-1} + (1-\xi) RD_{it} = (1-\xi) \sum_{\tau=0}^{\infty} \xi^{\tau} RD_{i,t-\tau} \tag{14}$$

where $\xi \in (0,1)$ is the memory parameter. By iterating, the long run internal R&D effort turns out to be a weighted average of past R&D expenditures, with exponentially decaying weights. In words, absorptive capacity is increasing with the firm's R&D long term effort and tends asymptotically to 1. Taking these assumptions into account, the knowledge stock, z_{it}, evolves according to[13]

$$z_{it} = (1-\delta^z) z_{it-1} + RD_{it} + (1 - e^{-\eta \overline{RD}_{it}})(\psi \sum_{j \neq i} RD_{jt}), \tag{15}$$

Note that absorptive capacity is firm-specific: firms' heterogeneity is key in the acquisition of external knowledge through spillovers.

Choice of vintage We assume that the *actual* productivity of a capital good of vintage v installed at firm i is determined by the *knowledge gap*:

$$g^v_{it} = \hat{A}^v_t - \hat{z}_{it}$$

[13] A similar formalization of the knowledge accumulation process was first proposed by Cohen and Levinthal (1989) to investigate both empirically and theoretically the twofold nature of R&D as a source of generation and absorption of technical knowledge. This hypothesis has been tested by Levin et al. (1987). Equation (15) is a streamlined variant of the original equation, that ignores the role of extra-industry spillovers and includes a depreciation rate, δ^z, which captures obsolescence of technological knowledge.

The knowledge gap is the difference between the state of "technical advancement" of the machine tool A^v – i.e., its potential productivity – and the firm's stock of technological knowledge, z_i, both normalized to fall in the interval [0,1].[14] Notice that, by construction, $g_{it}^v \in [-1, 1]$. We assume that the firm can fully exploit the productivity of vintage v – i.e., the actual productivity A_{it}^v of the machine tool of vintage v installed at firm i is equal to potential productivity A^v – if the knowledge gap is non-positive ($g_i^v \leq 0$), that is if the stock of technological knowledge is greater than or equal to the potential productivity of the machine tool. If the knowledge gap is positive, on the contrary, actual productivity is only a fraction of potential productivity and the fraction is decreasing with the size of the knowledge gap: the greater the knowledge gap the smaller actual productivity. On the basis of this assumption, we postulate the following *relative productivity-knowledge gap* relationship:

$$\frac{A_{it}^v}{A^v} = \begin{cases} 1 & \text{if } -1 \leq g_{it}^v \leq 0 \\ \frac{2}{1+e^{\gamma g_{it}^v}} & \text{if } \quad 0 < g_{it}^v \leq 1 \end{cases} \tag{16}$$

with $\gamma \geq 1$. This function is represented in figure 1. $\forall g_{it}^v \in [-1, 0]$ actual and potential productivity coincide. As soon as the knowledge gap materializes, actual productivity falls short of potential productivity and it keeps decreasing with the size of the gap.[15] An increase of γ reduces actual productivity for any given positive knowledge gap. For this reason we interpret γ as the *intensity of the knowledge constraint* on the adoption of new and better machines. Having computed the actual productivity for each vintage of capital, the firms' choice of capital goods follows a logit model (Dawid et al., 2019). The probability for firm i of selecting a machine of vintage v depends positively on its actual productivity, A_{it}^v, and negatively on its price, P_t^v:

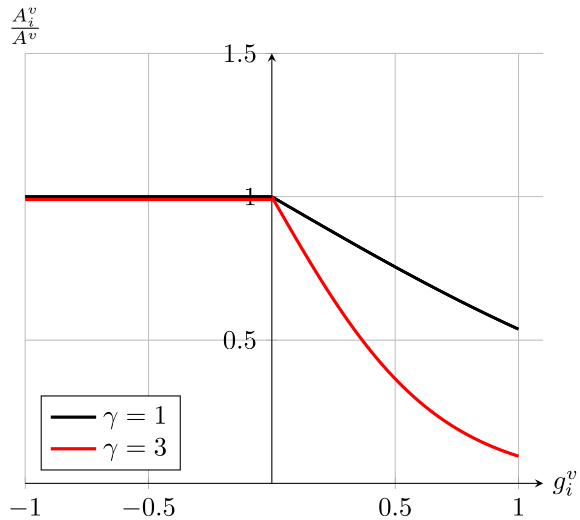
$$\mathbb{P}[\text{Firm } i \text{ selects vintage } v] = \frac{\exp\left[\beta(\eta_0 \log A_{it}^v - \eta_1 \log P_t^v)\right]}{\sum_{v=1}^{V} \exp\left[\beta(\eta_0 \log A_{it}^v - \eta_1 \log P_t^v)\right]} \tag{17}$$

where η_0 and η_1 are positive parameters and $\beta \in (0, \infty)$ is the *intensity of choice* of the capital good to purchase: the higher β, the faster the acquisition of the machine tool that provides the highest actual productivity to the adopting firm, given the machine's price. To simplify matters we

[14] Hatted variables are normalized by means of a min-max procedure. Let's denote the set of ordered firms' indicators of technical knowledge with $Z = \{z_1, z_2, ..., z_F\}$. Then $\hat{z}_i = \frac{z_i - \inf Z}{\sup Z - \inf Z}$ $\forall i = 1, 2, .., F$. The set of firms' normalized indicators of technical knowledge therefore is $\hat{Z} = \{0, \hat{z}_2, ..., 1\}$. Analogously, let's denote the set of ordered productivities of the different vintages of machine tools with $A = A^1, A^2, ..., A^V$. Then $\hat{A^v} = \frac{A^v - \inf A}{\sup A - \inf A}$ $\forall v = 1, 2, .., V$. The set of normalized productivities therefore is $\hat{A} = \{0, \hat{A}^2, ..., 1\}$.

[15] The maximum knowledge gap $g_{it}^v = 1$ is associated to the pair: $A^v = \sup A$ and $z_i = \inf Z$, that in turn generates the pair $\hat{A}^v = 1$ and $\hat{z}_i = 0$. In this case, the actual productivity of the machine tool will be a fraction $\frac{2}{1+e^{\gamma}}$ of actual productivity.

Figure 1: **Relative productivity and the knowledge gap**
The solid black (red) curve is the graph of (16) *when* $\gamma = 1$ *(*$\gamma = 3$*).*



set $\eta_0 = \eta_1 = 1$ so that we can simplify the equation above as follows:

$$\mathbb{P}[\text{Firm } i \text{ selects vintage } v] = \frac{\exp\left[\beta \log\left(\frac{A_{it}^v}{P_t^v}\right)\right]}{\sum_{v=1}^{V} \exp\left[\beta \log\left(\frac{A_{it}^v}{P_t^v}\right)\right]} \tag{18}$$

In this formulation, the probability that firm i selects a machine of vintage v depends on the quality/price ratio A_{it}^v / P_t^v. Equation (18) states that the probability is decreasing with the price and increasing with actual productivity. For any given price of the machine tool, firms with greater accumulated knowledge are more likely to choose more advanced capital goods. In the end, technological knowledge plays the role of a barrier to the use of high quality capital goods. Even if the price were low or financing abundant, so that the firm could have financial access to the high quality vintages, in the presence of insufficient technical knowledge the firm has an incentive to adopt and install low quality capital goods (Dosi and Nelson, 2010). In other words, there can be a *technological lock-in* effect.

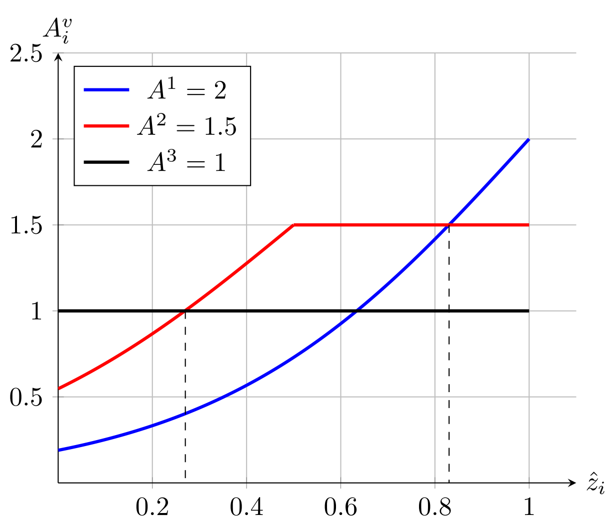
To illustrate this effect let's rewrite equation (16) as follows:

$$A_{it}^v = \begin{cases} A^v & \text{if } \hat{A}^v \leq \hat{z}_{it} \\ \dfrac{2A^v}{1 + e^{\gamma\left(\hat{A}^v - \hat{z}_{it}\right)}} & \text{if } \hat{z}_{it} < \hat{A}^v. \end{cases} \tag{19}$$

This function describes the relationship between (actual) productivity and (normalized) technological knowledge for any given pair A^v and $\hat{A}^v$. If $\hat{z}_{it} \geq \hat{A}^v$ actual and potential productivity coincide. As soon as the knowledge gap materializes, i.e., $\hat{z}_{it} \leq \hat{A}^v$, actual productivity falls short of potential productivity. However, actual productivity increases with technological knowledge.[16]

Consider a very simple setting with only three vintages, low quality ($A^1 = 1$ and $\hat{A}^1 = 0$), intermediate quality ($A^2 = 1.5$ and $\hat{A}^2 = 0.5$) and high quality ($A^3 = 2$ and $\hat{A}^3 = 1$). The productivity-knowledge line associated with the low quality vintage is depicted in black in figure 2. The red and blue lines represent the productivity-knowledge lines associated with the intermediate and high quality vintages respectively. The domain of the productivity-knowledge line is $0 \leq \hat{z}_{it} \leq 1$. Suppose, for the sake of discussion, that the price of the machine tools is uniform across vintages. In this case, the choice of the machine tool to buy depends exclusively on its actual productivity at the firm. From the figure it is immediate to infer that if knowledge at the firm is "low" ($0 \leq \hat{z}_{it} \leq 0.27$), the low quality vintage dominates the intermediate and high quality vintages because the actual productivity of the former at the firm is higher than the productivity of the latter. Poor organization or insufficient skills at the firm level therefore provide an incentive for the firm to buy and install the low quality machine because its performance is actually better (at the firm level) than machines of better quality. From the figure it is also straightforward to conclude that if $\hat{z}_{it} \in (0.27, 0.83)$, the intermediate quality vintage dominates the low and high quality vintages. Only if knowledge is "high" ($0.83 < \hat{z}_{it} \leq 1$) the firm should purchase the high quality vintage. Therefore the higher β, the faster the adoption of low (high) quality machine tools

Figure 2: **Productivity and technological knowledge**



[16]The upper bound on normalized technological knowledge is $\hat{z}_{it} = 1$. In this case, the actual productivity of the machine tool will be $\frac{2A^v}{1+e^{\gamma\left(\hat{A}^v - 1\right)}}$.

by firms with low (high) technical knowledge. For this reason the intensity of choice governs the *degree of knowledge specialization or polarization* among adopting firms.

3.5 Investment

Since capital is fixed in the short run – by assumption, machine tools purchased in t can be employed in the production process starting from $t+1$ – the firm's investment decisions ignore temporary fluctuations in demand and aim at achieving a desired level of aggregate *production capacity* "in the long run". To determine the desired production capacity, the firm estimates the long run desired scale of production $\bar{Y}_{i,t-1}$ by means of the following adaptive algorithm (applied to data collected over the entire life of the firm up to period t-1): $\overline{Y}_{i,t-1} = \nu\overline{Y}_{i,t-2} + (1-\nu)Y_{i,t-2}$ where $\nu \in (0,1)$. By iterating, it is easy to see that $\overline{Y}_{i,t-1}$ is a weighted average of past desired production levels as defined in equation (5) and therefore, in the end, of past sales and changes of inventories. Given a target utilization rate $\bar{\omega}$, desired production capacity in t will be $\frac{\bar{Y}_{it-1}}{\bar{\omega}}$. The firm purchases a new capital good of vintage v whenever desired production capacity exceeds the un-depreciated capital inherited from the past $\hat{K}_{it} = \sum_{v \in V_{it}} (1-\delta) k^v_{i,t-1} A^v_{i,t-1}$ where δ is the depreciation rate. Therefore, the demand for capital goods is determined by the difference between desired and current production capacity, given the effective productivity of the previously selected vintage, A^v_{it}:

$$I_{it} = \Big(\frac{\bar{Y}_{it-1}}{\bar{\omega}} - \hat{K}_{it}\Big)\frac{1}{A^v_{it}}. \tag{20}$$

The law of motion of capital at the firm level, taking into account the batch of heterogeneous machines, is given by

$$K_{it+1} = \sum_{v=1}^{V_{it}} (1-\delta) k^v_{it} + I_{it}. \tag{21}$$

3.6 Price setting

According to surveys on firms' price-setting behavior, markup pricing is the prevailing rule in the presence of imperfect competition and market power (Fabiani et al., 2005; Alvarez et al., 2006). Accordingly, we assume that C-firms set the price by charging a markup μ_{it} on unit labor cost w_t/B_{it}:

$$p_{it} = (1+\mu_{it})\frac{w_t}{B_{it}}. \tag{22}$$

where w_t is the nominal wage and B_{it} is labour productivity. We assume moreover that the price set is bounded from below by the average cost, which includes also the cost of capital and interest payments. In other words, the markup must be high enough to cover non-labour costs.
Recalling (9), we can rewrite the pricing rule as follows: $p_{it} = (1+\mu_{it})\frac{w_t}{\kappa A_{it}}$. Since the productivity

of labour is proportional to the average productivity of capital installed at the firm, the adoption of new and more productive machine tools will make the unit labor cost and the price fall, if the wage and the markup do not change. However neither the wage nor the markup are constant in our setting.

We assume that the benefits of technical progress accrue also to workers: the nominal wage evolves over time at the growth rate of aggregate productivity, measured by the ratio of GDP Y to employment N. In symbols:

$$w_t = w_{t-1}(1 + \alpha_w g_{t-1}). \tag{23}$$

with $g_{t-1} = \frac{Y_{t-1}}{N_{t-1}} / \frac{Y_{t-2}}{N_{t-2}} - 1$. α_w is the elasticity of the wage to aggregate productivity. It is easy to show that the latter is affected by the adoption of new technologies economy wide. Unit labour costs at firm i, therefore will change over time depending on the relative magnitude of the change in productivity economy-wide and at the firm. If productivity at the firm level grows faster than at the aggregate level, unit labour cost will fall and viceversa.

As to the markup, in line with Dosi et al. (2010a), we assume that the firm sets the markup depending on market power measured by the variation of market share (Kalecki, 1942). We postulate the following markup updating rule:

$$\mu_{it} = \begin{cases} \mu_{it-1}(1+\tilde{\mu}) & \text{if} \quad f_{it} > f_{it-1} \\ \mu_{it-1}(1-\tilde{\mu}) & \text{if} \quad f_{it} < f_{it-1} \\ \mu_{it-1} & \text{if} \quad f_{it} = f_{it-1} \end{cases} \tag{24}$$

where $\tilde{\mu}$ is a random draw from a Folded Normal distribution with parameters $(\mu_{FN_3}, \sigma_{FN_3})$ and f_{it} is the firm's market share. Equation (24) states that if the firm's market share grows, market power increases and the markup will be adjusted upward by a random growth rate $\tilde{\mu}$ and viceversa.

3.7 Profits, dividends and net worth

When the consumption goods market closes, C-firms compute profits as the difference between production value (sales proceedings and inventory change) and total costs (wage bill, capital and inventory depreciation, interest payments and R&D expenditure):[17]

$$\pi_{it} = p_{it}Q_{it} + (inv_{it}p_{it} - inv_{it-1}p_{it-1}) - w_t N_{it} + \tag{25}$$

$$- \sum_{v \in V_{it-1}} \delta p^v_{t-1} k^v_{it-1} - \hat{r}_{it} L_{it} - RD_{it} - \delta^{inv} inv_{t-1} p_{it-1}. \tag{26}$$

[17]Since the rate on loans extended by the bank to the i-th firm can vary over time, $\hat{r}$ is the weighted average of past interest rates with time-varying weights. See Assenza et al. (2015) for a detailed explanation.

If production value exceeds costs, the firm distributes a fraction θ of profits to the owner in the form of dividends and retains the residual within the firm. If costs exceed production value, the firm records a loss. In this case the firm does not distribute dividends. Retained profits therefore are $\pi^r_{it} = \max[(1-\theta)\pi_{it}, 0]$. Retained profits (if value exceed costs) or losses (if costs exceeds value) pile up to equity,[18] which evolves as

$$E_{it+1} = E_{it} + (1 - \mathbb{1}_\pi \cdot \theta)\pi_{it}. \tag{27}$$

where $\mathbb{1}_\pi$ is an indicator function that takes value 1 if $\pi_{it} > 0$, zero otherwise. When net worth turns negative or liquidity falls short of financial obligations, i.e., interests and debt installment, the firm goes bankrupt and exits. Since, by assumption, the number of firms is constant, each bankrupt firm is replaced by a new entrant, recapitalized by means of the owner's wealth. The cost of non-performing loans will be borne by the bank, whose equity will be reduced accordingly (see below, section 3.10).

3.8 K-firms

K-firms, indexed with $j = 1, 2, ...F_k$, supply machine tools and demand labour and credit. There are F_k "brands" of machine tools because every K-firm produces a specific brand. In the initial state of the economy, the cardinality of the set of K-firms coincides with the cardinality of the set of vintages ($V_0 = F_k$) because each K-firm produces the initial vintage of the machine tool of the associated brand. The quality of the machine tools of a given brand, however, is time-varying because the K-producer can increase the productivity of the machine tools by means of innovation/imitation. A new vintage of a machine tool of a certain brand, therefore, will be characterized by higher productivity. While the number of K-firms is constant, the cardinality of the set of vintages is time varying because each K-firm is in principle producing more than one vintage of machine tools. Of course, machine tools of the same brand and different vintages can co-exist as they are durable and depreciate only by a fraction $\delta \in (0, 1)$ per period.

The behavioural rules concerning the determination of expected demand, desired production and labour demand described above for C-firms apply also to K-firms. Similarly to C-firms, the

[18] To check that the balance sheet identity holds in every period, we compare the level of net worth as computed in equation (27) with the one resulting from the difference between assets and liabilities. Firms' assets are given by the sum of capital value and liquidity, while liabilities consist of corporate debt. Liquidity is updated by taking into account all cash inflows and outflows, including debt installments, as shown in the Appendix.

desired output of K-firms is based on their expected demand:[19]

$$\tilde{Y}_{jt} = Q^e_{jt}(1+\iota) - inv_{jt-1}, \tag{28}$$

$$Q^e_{jt} = Q^e_{jt-1} + \rho(Q_{jt-1} - Q^e_{jt-1}). \tag{29}$$

In order to produce, the firm uses only labour N_{jt} and a linear technology

$$Y_{jt} = B_{jt}N_{jt} \tag{30}$$

where B_{jt} is the productivity of labour.

Innovation and imitation Each K-firm is characterized by a *technological profile* $(A^v_{jt},\ B_{jt})$, consisting of the productivity of the machine tool of vintage v produced by firm j and the productivity of labor employed at firm j. Innovators strive to improve the 'quality' of their profiles. To do that, they invest a fraction $\sigma \in (0,1)$ of past retained profits in R&D. The fraction $\chi \in (0,1)$ of R&D expenditure is allocated to imitation of new technologies generated by other K-firms while the fraction $(1-\chi)$ of R&D expenditure is devoted to in-house generation of new technologies. In symbols:

$$RD_{jt} = \sigma\pi^r_{jt-1}, \tag{31}$$

$$IN_{jt} = (1-\chi)RD_{jt}, \tag{32}$$

$$IM_{jt} = \chi RD_{jt}. \tag{33}$$

In line with the evolutionary literature (Nelson and Winter, 1982; Dosi et al., 2010a), innovation and imitation activities follow a two-step stochastic process.

The first step determines whether or not the firm has the opportunity to innovate/imitate and consists in a random draw from a Bernoulli distribution with probabilities Pr^{inn}_{jt} and Pr^{imi}_{jt} defined as follows

$$Pr^{inn}_{jt} = 1 - e^{-\zeta^{inn} IN_{jt}}, \tag{34}$$

$$Pr^{imi}_{jt} = 1 - e^{-\zeta^{imi} IM_{jt}}, \tag{35}$$

where ζ^{inn} and ζ^{imi} are positive parameters that capture the capacity of the K-firm to innovate and imitate respectively. The probability of innovation (imitation) is increasing with R&D expenditure allocated to innovation (imitation), concave and tending asymptotically to 1. The higher ζ^{inn} (ζ^{imi}), the higher the probability to innovate (imitate) for any given level of R&D expenditure in

[19]Inventories of machine tools evolve according to the following law: $inv_{jt} = inv_{jt-1}(1-\delta^{inv})$.

innovation (imitation). Since ζ^{imi} is uniform across K-firms, we can interpret this parameter as the *degree of knowledge diffusion among K-firms*, due to the capability of each K-firm to appropriate through imitation the new knowledge (embodied in capital goods) generated by its K-competitors.

In the second step, the firm that has got access to innovation draws a pair of productivity gains (Δ_A, Δ_B) from a Folded Normal distribution. The profile of the innovating j-th firm, therefore, evolves as follows

$$A^v_{jt+1} = A^v_{jt}(1 + \Delta_A), \text{ where } \quad \Delta_A \sim FN(\mu_{FN_1}, \sigma^2_{FN_1}), \tag{36}$$

$$B_{jt+1} = B_{jt}(1 + \Delta_B), \text{ where } \quad \Delta_B \sim FN_2(\mu_{FN_2}, \sigma^2_{FN_2}). \tag{37}$$

Innovation therefore yields an increase of both the productivity of the new vintage of machine tools produced by firm j, and of the productivity of labor employed at firm j.
The firm that has got access to imitation, on the other hand, will search among the top ranking Z_{imi} technically advanced K-firms and randomly picks one of their technological profiles. The probability to imitate a given K-firm is decreasing with the technological distance between this firm and the j-th firm, multiplied by the parameter λ^{imi}. The technological distance is the percent deviation of the productivity of the machine tool produced by the given K-firm from the j-th firm.

Finally, firms compare the outcomes from innovation and imitation processes and choose the profile with the highest built-in productivity.

Labor demand K-firms need workers to carry out both production and R&D activities. The research budget RD_{jt} is used to hire research workers: $N^R_{jt} = \frac{RD_{jt}}{w_t}$. As to production workers, based on desired output, the firm has the following labour requirement:

$$\tilde{N}_{jt} = \frac{\tilde{Y}_{jt}}{B_{jt}}. \tag{38}$$

Job vacancies are then posted in the labor market:

$$J_{jt} = \max(\tilde{N}_{jt} - N_{jt-1}, 0) + \mathbb{1}_R \frac{RD_{jt}}{w_t} \tag{39}$$

Price setting Similarly to C-firms, capital good producers set the price by charging a markup over unit cost w_t/B_{jt}. However, differently from C-firms, the markup of K-firms is assumed to be fixed, as in Dosi et al. (2010a). Hence, the capital good price is given by

$$p_{jt} = (1 + \bar{\mu})\frac{w_t}{B_{jt}}, \tag{40}$$

where $\bar{\mu}$ is constant and uniform across K-firms. Notice that when the firm innovates or imitates, both the productivity of the machine tool produced and the productivity of labour used to produce it increase. Therefore innovation/imitation reduces the unit cost of labour at successful K-firms. In the end, product innovation/imitation by the K-firm translates into process innovation both at the firm that introduces innovation and at the firm that adopts it.

Profits, dividends and net worth Profits (or losses) are computed as the difference between production value and total costs.

$$\pi_{jt} = p_{jt}Q_{jt} + (inv_{jt}p_{jt} - inv_{jt-1}p_{jt-1}) - w_t N_{jt} + \tag{41}$$

$$- \hat{r}_{jt}L_{jt} - RD_{jt} - \delta^{inv} inv_{jt-1}p_{jt-1}. \tag{42}$$

If production value exceeds costs, the firm distributes a fraction θ of profits to the owner in the form of dividends and retains the residual within the firm. If costs exceed production value, the firm records a loss. In this case the firm does not distribute dividends. Retained profits therefore are $\pi^r_{jt} = \max[(1-\theta)\pi_{jt}, 0]$. Equity evolves as follows:

$$E_{jt+1} = E_{jt} + (1 - \mathbb{1}_\pi \cdot \theta)\pi_{jt}. \tag{43}$$

When net worth turns negative or liquidity falls short of financial obligations, the firm goes bankrupt and exits. Each bankrupt firm is replaced by a new entrant, recapitalized by the owner's wealth. The cost of non-performing loans will be borne by the bank.

3.9 Households

The household sector is composed of W workers and $F = F_c + F_k$ firm owners. Each worker supplies one unit of labor in exchange for a wage. The worker's disposable income is $Y_{w,t} = \mathbb{1}_e(1-\tau^w)w_t + (1-\mathbb{1}_e)s_u w_t$, where $\mathbb{1}_e$ is an indicator function that takes value 1 if the worker is employed, 0 otherwise; $\tau^w \in (0,1)$ is the tax rate on labor income; $s_u \in (0,1)$ is the replacement rate for the unemployment subsidy and $s_u w_t$ are unemployment benefits.

The disposable income of the firm owner coincides with after tax dividends: $Y_{f,t} = (1-\tau^f)\theta \cdot \mathbb{1}_\pi \pi_{f,t-1}$, $f = 1, 2, ...F$, where τ^f is the tax rate on dividends. Also the bank's profit are distributed to firm owners and taxed at the same rate. If the bank records a loss, shareholders will not receive dividends.

The household's demand for consumption goods is a linear function of disposable (after-tax) income and financial wealth (deposits). We assume that workers and firm owners have different propensities to consume out of income, namely c_w and c_f, with $0 < c_f < c_w < 1$. [20] We denote

[20] The numerical values of c_w and c_f we set for simulation purposes (0.9 and 0.6 respectively) correspond to

the propensity to consume out of financial wealth with $c_d \in (0, 1)$, uniform across income groups, and deposits with D_h, $h = w, f$. Planned expenditure on consumption goods therefore is

$$C_{h,t} = c_h(1 - \tau^h)Y_{h,t} + c_d D_{ht-1}. \tag{44}$$

where $h = w, f$. Unspent income (household saving) in t translates into additional deposits.

Each household aims at achieving the desired level of consumption by means of purchases on the market for C-goods. The choice of the seller follows a preferential attachment scheme. In period t, household h compares the price paid in period $t-1$ (charged by the previous seller, firm i) – denoted with $P_{i,t-1}$ – with the lowest among the prices charged by $Z_c - 1$ C-firms (competitors of firm i) visited in period t, denoted with $P_{z,t}$, $z = 1, 2, ..., Z_c - 1$, $z \neq i$. If the latter is lower than the former, the consumer will switch to the new supplier with a certain probability, $Pr^s_{h,t}$, which is increasing with the gap between $P_{i,t-1}$ and $P_{z,t}$ (see Delli Gatti et al. (2010) for details). In symbols: $Pr^s_{h,t} = 1 - e^{-\beta_s \frac{P_{z,t} - P_{i,t-1}}{P_{z,t}}}$. The parameter $\beta_s > 0$, measures the *intensity of choice*, i.e., how fast consumers switch to the most convenient supplier.
If the quantity of goods supplied by the selected seller in each period is smaller than planned consumption, the household will buy at the other $Z_c - 1$ firms ranked in ascending order based on price. If planned consumption is not achieved (due to insufficient supply at the visited firms), the household saves involuntarily.

3.10 Banking system

As we anticipated, for simplicity the banking system is represented by a single bank that receives funds from households and firms in the form of deposits (not remunerated), extends loans to firms and purchase Government bonds. Given the focus of the present paper, we have greatly simplified the behavioural assumptions concerning banks with respect to Assenza et al. (2015) and Terranova and Turco (2022).

The bank sets the interest rate r_{ft} and the size of the loan $\mathcal{L}_{ft}$, $f = 1, 2, ..., F$ on the basis of the firm's financial conditions.[21]

The bank is subject to prudential regulation. First of all, total credit L_t (sum of bank exposure to all the firms) is constrained by the bank's equity E^b_t: $\varepsilon_1 L_t \leq E^b_t$ where ε_1 is the minimum (aggregate) capital requirement. Second the bank's exposure to a single firm cannot exceed a fraction ε_2 of equity: $L_{ft} \leq L^{max}_{ft} = \varepsilon_2 E^b_t$.[22]

The interest rate charged by the bank to each firm is determined by adding to the risk free rate

those found by Dynan et al. (2004), for an individual belonging to the third quintile of income distribution and an individual belonging to the top 5% respectively.

[21]Denoting with L_{ft} credit outstanding (the stock of debt), by construction $\mathcal{L}_{ft} = L_{ft} - L_{ft-1}$.

[22]Mimicking the Basel rule we set $\varepsilon_1 = 0.08$ and $\varepsilon_2 = 0.25$.

r a markup corresponding to the firm's leverage λ_{ft}:

$$r_{ft} = r(1 + \lambda_{ft}), \tag{45}$$

where $\lambda_{ft} = \frac{L_{ft}}{E_{ft}+L_{ft}}$.

The actual size of the loan is the minimum between the firm's credit demand, F_{ft} (the financing gap), and the maximum size of the loan set by the bank:

$$\mathcal{L}_{ft} = \min(\mathcal{L}_{ft}^{max}, F_{ft}). \tag{46}$$

According to equation (46), the borrowing constraint on the firm is binding whenever $F_{ft} > \mathcal{L}_{ft}^{max}$. In this case, the firm will be forced to down-size to bring the actual scale of activity in line with the availability of funds.

The firm's loan is repaid in installments. Denoting with ρ_L the rate of reimbursement of *outstanding* debt, in each period, the borrower repays a fraction $\rho_L(1-\rho_L)^t$ of principal and interests. Hence, the loan will be completely reimbursed only asymptotically on an infinite time horizon. If the firm turns out to be insolvent, it will go bankrupt and exit. Non performing loans will be accounted for in the determination of the bank's equity. For simplicity, we assume that the bank is willing to purchase all the bonds issued by the Government at a given risk free rate.

The bank's revenues are the sum of interest payments by solvent firms and interest payments by the Government. Profits are negatively affected by non-performing loans. A fraction θ of bank's profits (if positive) is distributed to firm owners. Retained profits allow to increase net worth.

4 The drivers of the decline in business dynamism

In order to shed light on the mechanisms underlying the decline in U.S. business dynamism we follow a two-step procedure (described in detail in section 4.1). First, we calibrate and validate a *baseline scenario*, which captures the empirical patterns of the U.S. economy prior to 1980. Second, we construct an alternative scenario characterized by *Low knowledge Diffusion* (LD) by changing the calibration of a set of key parameters governing the degree of knowledge diffusion both in imitation among K-firms and in technology adoption among C-firms in order to replicate the stylized facts characterizing the post-1980 decline in business dynamism.

By comparison, the baseline will be referred to also as the High knowledge Diffusion (HD) scenario. The precise meaning of these expressions will be specified momentarily. By conducting this two-step calibration, we are able to investigate the transition to a more concentrated economy and explore the economic mechanisms at different levels of aggregation (section 4.2). In section 4.3, we conduct a comprehensive sensitivity analysis by systematically varying the key parameters.

Par	Description	Baseline (High KD)	Alternative (Low KD)
λ^{imi}	Sensitivity of imitation to technological distance	1	5
ζ^{imi}	Imitation capacity	0.3	0.01
β	Intensity of choice of K-goods	0.1	1
γ	Intensity of knowledge constraints	1	3

Table 1: Baseline and alternative scenarios

This provides a deeper understanding of the drivers of business dynamism.

4.1 Calibration and validation

To calibrate the baseline scenario, we choose a combination of numerical values of parameters that allows to replicate the empirical regularities observed in the U.S. macroeconomic data from Q1 1959 to Q4 1980, namely trend, cyclical fluctuations, and auto- and cross-correlations of key variables (GDP, consumption, investment and unemployment).[23] The parameter configuration for the baseline scenario is presented in Table 3 in the Appendix.

Next, we calibrate the alternative scenario by modifying four key parameters as shown in Table 1. As to K-firms, the calibration of LD (relative to the baseline) is characterized by (i) a lower degree of knowledge diffusion among K-firms due to a lower imitation capacity (ζ^{imi}); (ii) a higher sensitivity of imitation to the technological distance (λ^{imi}). As to C-firms, the calibration of LD is characterized by (i) a higher intensity of choice of capital goods (β) that measures the degree of knowledge polarization among C-firms and (ii) a higher intensity of the knowledge constraint (γ).

Table 2 displays the average values of key variables for the 1980s and 2010s and their percentage point variation computed on real world macroeconomic data and on artificial data generated by the simulations. As to the empirical evidence, we computed the average GDP growth rates for the intervals 1958-1980 and 1981-2020 from the FRED database. The concentration indicators comes from (Akcigit and Ates, 2021), and are based on (Autor et al., 2020). They refer to the years 1980 and 2010. The data on markups come from De Loecker et al. (2020), who report values for the years 1980 and 2016. Finally, the labor share of income comes from Guerriero (2019), who refers to the average values in the decades 1980s and 2010s.

In order to generate the artificial data, we first run the model for 1000 time steps using the baseline calibration. We discard the transient period consisting of the first 100 periods. We then run the model for 260 additional periods (quarters), to mimick the 65 years interval 1955-2020. The baseline scenario runs for the first 25 years, until 1980, after which we activate the alternative scenario, running for the remaining 160 quarters, i.e., 40 years until 2020. The GDP's growth rates for 1980s and 2010s are then computed by averaging the quarterly growth rates in the first 25 years

[23]We adopt the standard validation procedure for ABMs (Delli Gatti et al., 2018). The details of this procedure can be found in Appendix A.

Variable (%)	Empirical			Simulated		
	1980s	2010s	Δ	1980s	2010s	Δ
GDP growth	3.80	2.65	-1.15	3.97	2.28	-1.69
Concentration	38	43.5	5.5	7.73	17.27	9.54
Markup	1.2	1.61	0.41	1.33	1.47	0.15
Labor share	75.36	70.9	-4.46	77.96	74.14	-3.82

Table 2: Comparison between empirical and simulated variables in the period 1980-2010

and the following 40 years of the simulation. The remaining three variables shown in Table 2 are computed as the mean across Monte Carlo simulations at time step 200 (1980) and 360 (2020). Our framework does a pretty good job in replicating the decline in GDP growth rate and the labor share and the increase of the average markup after 1980. The model struggles to precisely match the empirical concentration *levels* in the 1980s and 2010s – due to the assumption of a constant number of firms – but it captures the magnitude of the *change* observed in the empirical data fairly well.

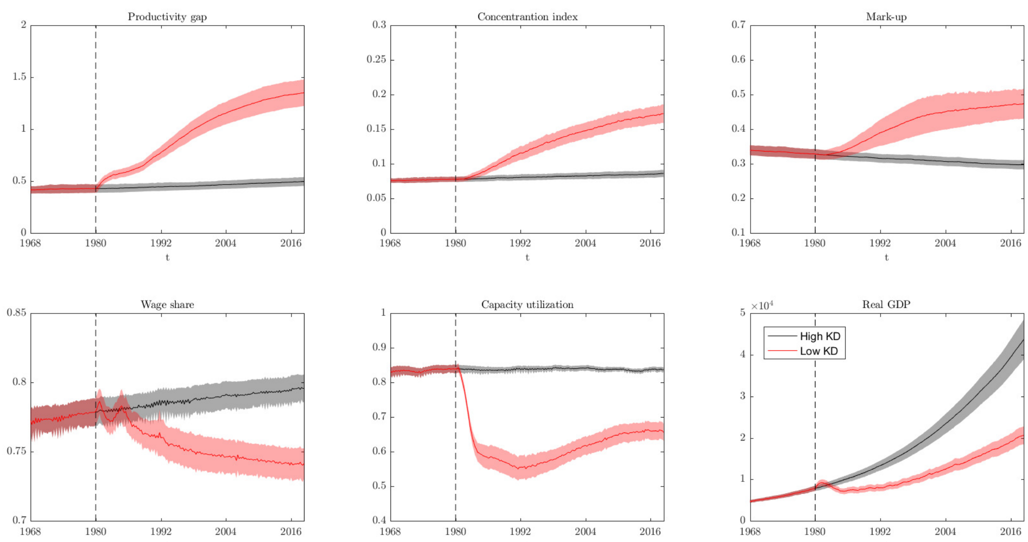


Figure 3: Evolution of macroeconomic variables under the baseline (high knowledge diffusion, black) and alternative (low knowledge diffusion, red) scenarios. Mean and confidence interval from 100 Monte Carlo simulations.

Figure 3 illustrates the emergent macroeconomic dynamics succinctly summarized in Table 2. The figure depicts the average simulation run across 100 MC simulations and its confidence intervals for key variables in both the baseline (black) and alternative (red, from 1980) scenarios.

The figure clearly illustrates that under the baseline scenario the economy is in a competitive state, characterized by a low and stable productivity gap and concentration level in the consumption goods sector, which prevents C-firms from exploiting their market power. This leads to a slightly declining average markup and an high and increasing labor share of income. The economy experiences roughly constant capacity utilization and noticeable GDP growth rate.

Under the alternative scenario characterized by low knowledge diffusion and high technical polarization, the economy experiences an increasing concentration driven by widening productivity gap among firms. Under low knowledge diffusion, in fact, large knowledge-intensive firms are more likely to adopt and make efficient use of the best technologies, thus obtaining a competitive advantage. Their increased market power translates into higher weighted-average markups and lower labor share of income. Capacity utilization undergoes a significant decline and eventually stabilizes approximately 15 percentage points below that of the baseline scenario. This is due to the fall in labour share, that reverberates on the demand for C-goods (since workers have the highest propensity to consume). The panel illustrating GDP dynamics shows a decline in the growth rate leading to a much lower GDP by the end of the 2010s.

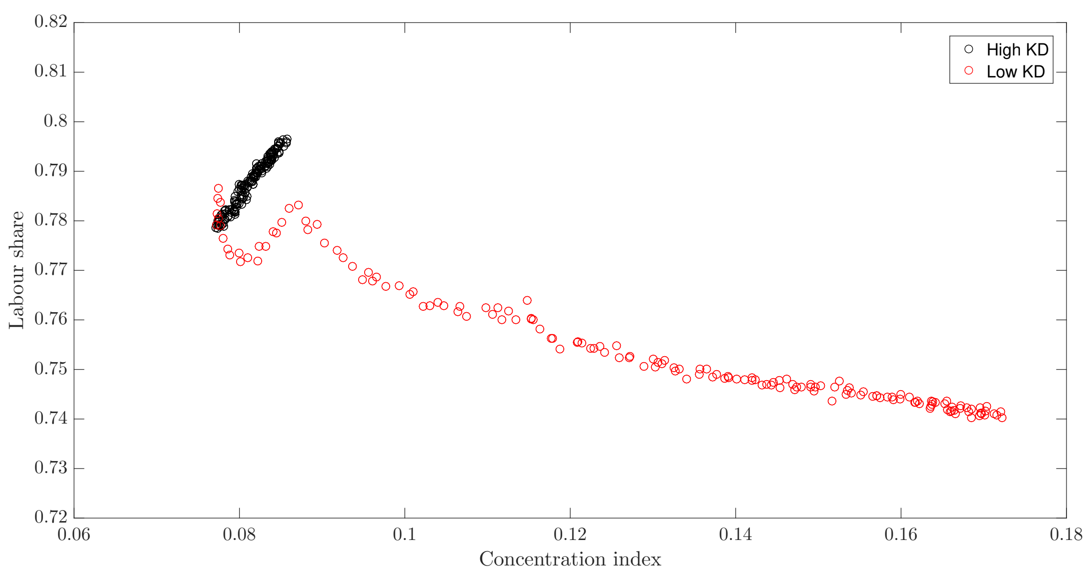


Figure 4: Correlation between concentration index and labour share under the baseline (high knowledge diffusion, black) and alternative (low knowledge diffusion, red) scenarios. Pooled quarterly observations from 100 Monte Carlo simulations.

Figure 4 shows the correlation between the labor share of income and an indicator of market concentration, namely the four-firm concentration ratio (i.e., the market share of the four largest firms of the industry), in the baseline (black) and alternative (red) scenarios. In the baseline, both the concentration indicator and labour share are characterized by a very modest increase. The positive correlation therefore mirrors this joint pattern. On the contrary, in the alternative scenario, a higher concentration index results from a less competitive and dynamic economy, where large firms utilize their market power to raise their markups at the expense of workers' real wages, leading to a decline in the labor share of income.

In sum, under the alternative scenario with low knowledge diffusion, the model is able to replicate 6 of the 10 stylized facts characterizing the decline in business dynamism highlighted by Akcigit and Ates (2021), namely: (1) Market concentration has increased; (2) Markups have increased; (3) Profit share of GDP has increased; (4) Labor share of GDP has decreased; (5) Market concentration and labor share are negatively associated; (6) Productivity gap between leaders and laggards has widened.[24]

4.2 Microeconomic behaviour and emerging properties

In this section, we fully exploit the granularity of the agent-based model to investigate the microeconomic mechanisms driving the divergent macroeconomic dynamics shown above. We examine the evolution of micro variables from a representative simulation in the baseline and alternative scenarios, shown in Figures 5 and 6, respectively. In the baseline, each K-firm can easily imitate the new machine tools produced by competitors. As a result, there is rapid convergence of the productivities of different vintages, as shown in the upper-left panel of Figure 5. In the consumption goods sector, although a handful of firms is able to accumulate remarkable technical knowledge, they do not gain a significant advantage over other firms. This is due to modest technical polarization and limited impact of knowledge constraints on capital goods usage. Consequently, market shares and markups are low and not markedly different across C-firms (lower panels). This implies that, while some firms may outperform others in terms of productivity, the differences in market power and pricing strategies are modest.

Dynamic patterns are starkly different under the alternative scenario. The productivity of machine tools diverges over time due to limited imitation as shown in the upper-left panel of figure 6. This translates into widening productivity gap among C-firms (upper-right panel) because of the higher degree of knowledge specialization in technology adoption. In fact, high (low) knowledge-intensive firms are more likely to choose the best (worst) vintage of capital goods (see section

[24] The remaining four empirical regularities are: (7) Firm entry rate and share of young firms in economic activity have declined; (8) Job reallocation and churn have slowed down; (9) The dispersion of firms growth rates has gone down; (10) The productivity growth has fallen. Admittedly, our model does not do a good job in replicating the lower entry rate and job reallocation observed in the post-1980s period. Due to the assumption of one-to-one replacemet of an exiting firm with an entrant, the baseline scenario is characterized by a low number of firm defaults and thus new entrants, whereas in the alternative scenario the opposite is true, leading the employment rate of new firms to be higher. The model is also not well equipped to capture the lower growth dispersion because, in the alternative scenario, large firms are able to keep their growth rates relatively high.

3.4). This triggers a reallocation of market shares towards the more productive and knowledge-intensive firms, leading to higher market concentration. In the artificial data, therefore, we observe a tendency that mimicks the expansion of "superstar firms" highlighted by Autor et al. (2020).

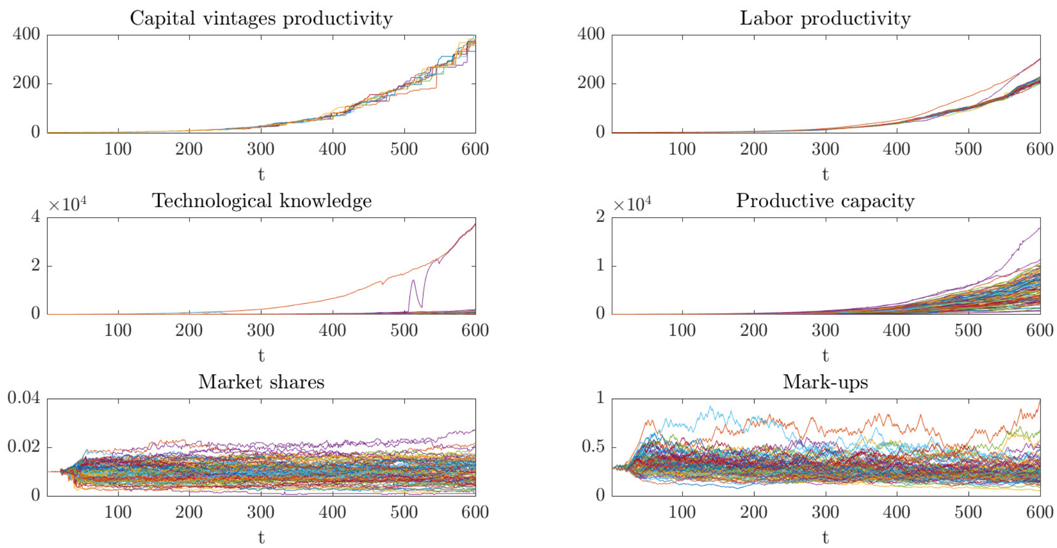


Figure 5: Evolution of microeconomic variables under the baseline scenario with high knowledge diffusion from one representative simulation.

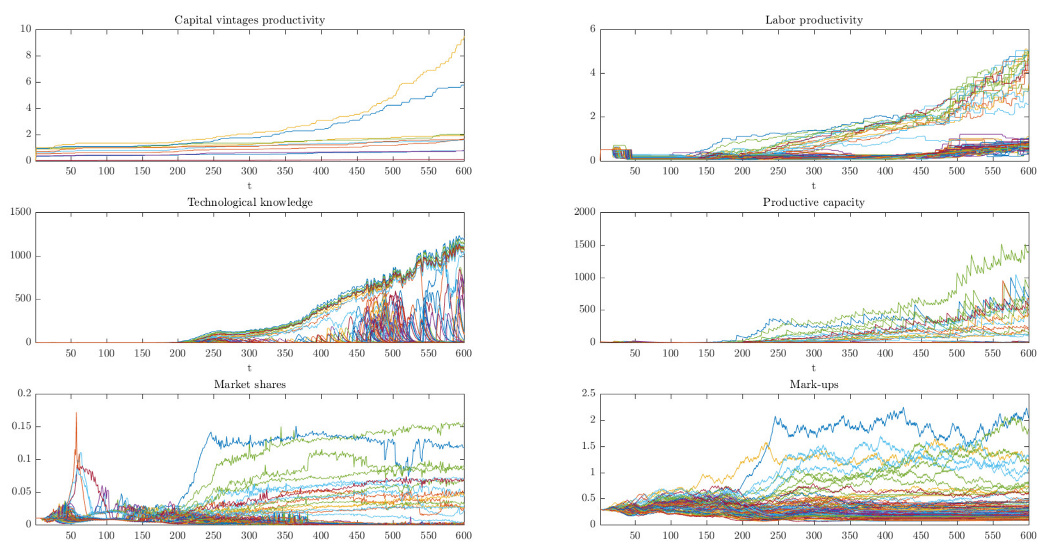


Figure 6: Evolution of microeconomic variables under the alternative scenario with low knowledge diffusion from one representative simulation.

The evolution of market concentration, therefore, can be traced back to the decline in knowledge diffusion both among K-firms (due to the implicit obstacles to imitation) and among C-firms (due to the polarization in technology adoption). Under this scenario, persistent technological discontinuities enable giant firms to consolidate their dominant position, increase market shares and charge higher markups.

4.3 Sensitivity analysis

In this section, we perform a sensitivity analysis on the knowledge-related parameters we have chosen to characterize scenarios in order to assess the contribution that each one of them provides in explaining the results. We carry out two experiments.

In the first experiment, we examine the effects of a change in the intensity of choice β for different values of the intensity of knowledge constraint, γ.[25] In the second experiment, we analyze the effects of a lower capacity to imitate among K-producers for different configurations of technology adoption by C-firms. In particular, we test the impact of a decline in imitation capacity, ζ^{imi}, for different combinations of β and γ.[26]

We perform 100 Monte Carlo simulations for each experiment's parameter sweep. The cross-MC distribution for the final 500 simulation time steps is then gathered.

Figure 7 presents the findings from the first experiment. It shows the effects of a rise in β on GDP growth rate, wage share, productivity gap and concentration index (for both the consumption and capital goods sector) for various intensities of knowledge constraint γ. From the figure, we infer that, when the intensity of the knowledge constraint is very low ($\gamma = 1$, blue bars), higher β results in faster GDP growth as well as higher productivity gap and concentration index in the K-sector, but not in the C-sector.

Conversely, in the presence of high knowledge constraints ($\gamma = \{3, 5\}$, green and magenta bars), higher β results in a lower increase in growth and has opposite effects on the industrial dynamics, leading to an increase in the productivity gap and market concentration in the C-sector, but not in the K-sector. The reason can be found in the impact that knowledge specialization has on the process of adoption and diffusion of technologies and, consequently, on market structure. The effect on market structure varies across sectors depending on the intensity of the knowledge constraint.

[25] We consider the following set of numerical values: $\beta = \{0.1, 0.5, 1\}$, $\gamma = \{1, 3, 5\}$. The baseline scenario is characterized by $\beta = 0.1$ and $\gamma = 1$.

[26] In this experiment, we keep λ_{imi} constant at the level corresponding to the LD scenario. We consider the following sets of numerical values: $\zeta^{imi} = \{1.8, 0.5, 0.01\}$, $(\beta, \gamma) = \{0.1, 1; 1, 1; 1, 5\}$.

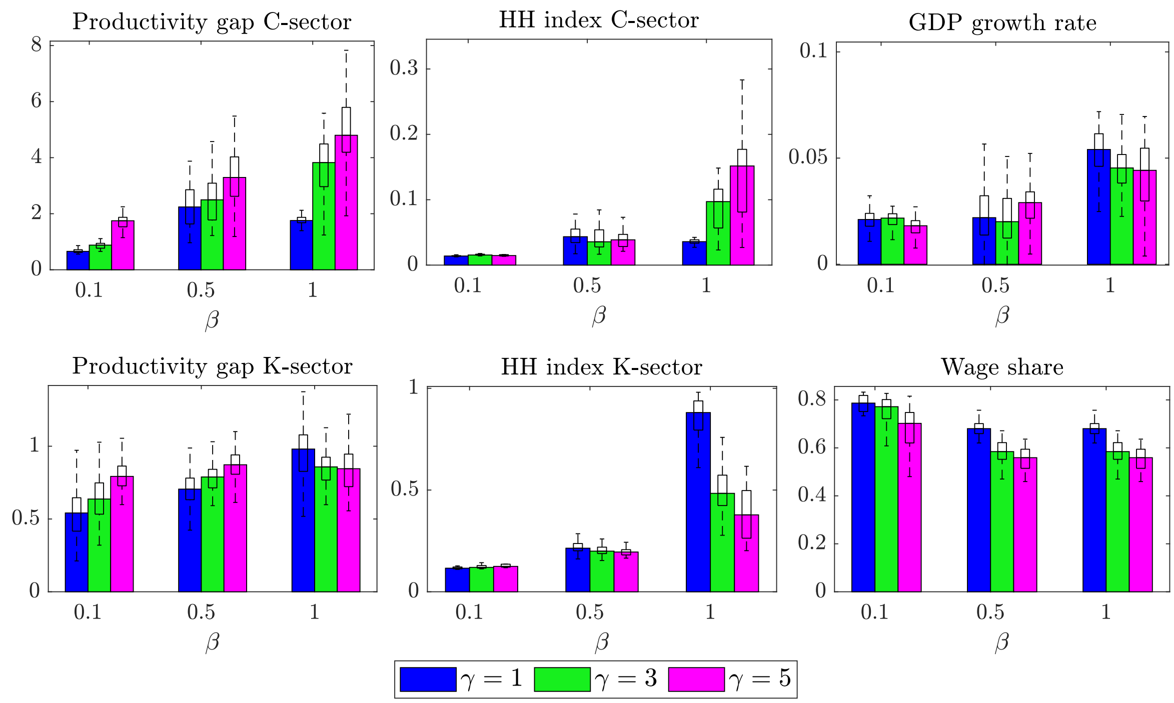


Figure 7

As β increases, high knowledge intensive firms in the C-sector (C-leaders) are more likely to adopt the most productive capital vintages, whereas low knowledge intensive firms (C-laggards) are more likely to adopt the least productive ones. As the C-leaders have a higher propensity to invest than the C-laggards, higher specialization implies an increase in the overall demand for the best capital vintages, which, by encouraging the innovative effort of their producers (K-leaders), results in new product and process innovations. This leads to higher productivity and lower price of the best vintages. Consequently, if the knowledge constraint is very low ($\gamma = 1$), the best technique becomes dominant (higher concentration index in the K-sector) as all C-firms will find it technologically and economically convenient to adopt it.[27]

On the contrary, if the knowledge constraint is stringent ($\gamma = \{3, 5\}$), C-laggards will find it technologically impractical to install the best machine tools due to the high knowledge gap and will turn instead to other, less productive vintages. As a result, the best vintage will not become dominant in the market for K-goods (lower concentration index in the K sector) because only the C-leaders will be able to adopt it. This leads to higher concentration and productivity gap in the

[27]The ratio of effective productivity to price that governs the probability of buying the best technique (equation (18)) will be greater than any other vintage. As long as the capital good price is low enough, this holds true for all sorts of C-firms regardless of their knowledge gap (that affects effective productivity).

C-sector, resulting in greater market power and lower wage share.

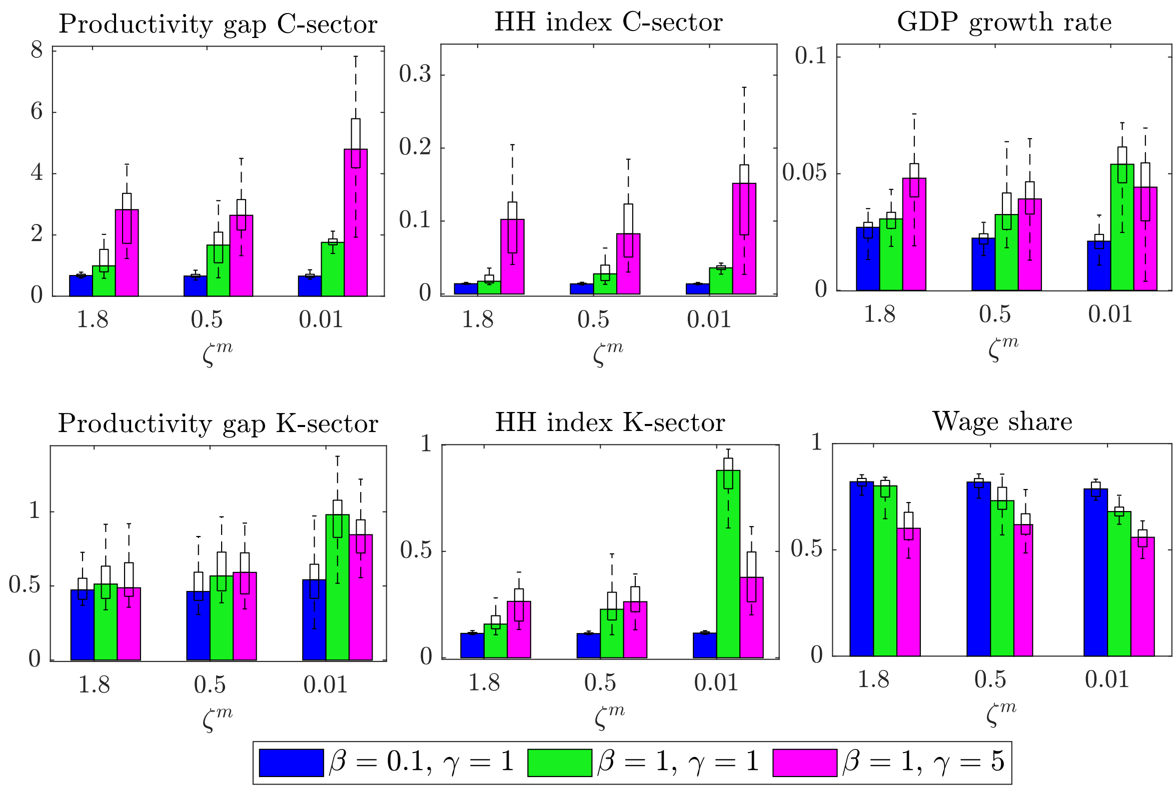


Figure 8

In other words, knowledge polarization promotes growth as long as the knowledge constraint is not too tight. By stimulating the innovative effort of the best K-producers, a higher level of knowledge polarization among C-firms will enable the best vintage to emerge provided its price is low enough to make it both economically and technologically advantageous for all firms. On the contrary, if the knowledge constraint is overly tight, the laggards with a greater knowledge gap will be penalized, resulting in higher productivity gap and stronger market concentration that benefit the leaders only, with negative effects on growth.

The results of the second experiment are shown in Figure 8. We examine the implications of a decline in the K-producers' capacity to imitate, captured by a decreasing ζ^{imi}. We consider three scenarios: (1) unconstrained (low β, low γ); (2) intermediate (high β, low γ) and (3) constrained (high β, high γ). From Figure 8 we infer that only in the constrained case ($\beta = 1, \gamma = 5$) the reduction in imitation ability produces effects that are consistent with declining business dynamism, such as a wider productivity gap and a greater market concentration in the C-sector, which is linked with lower wage share and declining growth. Indeed, in the unconstrained scenario, a smaller ζ^{imi} has almost no influence on key variables while it has a beneficial impact on GDP in the intermediate case. The reason is the following. In the unconstrained case (low β, low γ), where capital goods selection is nearly random and not strongly influenced by the knowledge gap, the investment demand coming from C-firms is evenly distributed among K-firms, promoting a convergence between capital goods (constant productivity gap in the K-sector). This in turn leads to a constant productivity gap and market concentration also in the C-sector. In the intermediate case (higher β), instead, the best technique becomes dominant (high concentration in the K-sector) provided that the knowledge constraint is sufficiently soft (low γ), for the reasons outlined in the first experiment. Consequently, the diffusion of the best technique among C-firms accelerates growth while limiting market concentration. Hence, only in the constrained case (high β, high γ) does a decline in imitation ability exacerbate the productivity differences between C-firms. In this scenario, only the leading firms have access to the best vintages, resulting in greater concentration, higher markup, and slower growth.

Interestingly, our findings challenge the perspective put forth by Akcigit and Ates (2021) as they suggest that a decrease in imitation ability alone can fully account for the observed decline in economic dynamism. Instead, our results indicate that a decline in knowledge diffusion is required not only in the imitation process among K-firms but also in technology adoption among C-firms.

5 Patents

The decline in knowledge diffusion can be explained, at least in part, by the strengthening of patent protection (Akcigit and Ates, 2023) that inhibits imitation, limiting the flow of knowledge across K firms. This trend is documented by evidence that shows an exponential increase in patenting since the 1980s, as a consequence of the Bayh-Dole Act of 1980 that enlarged the domain of patentability and softened the criterion of novelty (Dosi et al., 2023b). Moreover, the share of patents held by the top 1% innovative firms has dramatically increased, indicating an increase in patenting concentration (Akcigit and Ates, 2021).

In this section we assume that K-firms can patent their technological innovations to prevent competitors' imitation. A patent is characterized by two key parameters: *length* (τ^l) measured by the number of periods the patent remains valid, and *breadth* (τ^b) that enters the interval of innovations (i.e., new vintages of machine tools) protected by the patent. Following Dosi et al. (2023c), we define the *protected interval* $\mathcal{P}_j$ as the range of the productivity A_j of new vintages of machine tools (generated by innovation) protected by the patent. In symbols:

$$\mathcal{P}_j = \{A_j | A_j^v \cdot (1 - \tau^b) < A_j < A_j^v \cdot (1 + \tau^b)\} \tag{47}$$

Hence, the parameters τ^b and τ^l determine the strength of patent protection: the higher these parameters, the stronger the protection granted by the patent. The patent prevents imitation and forbid competitors' innovations whose productivity level falls within the protected interval (*protection effect*). On the other hand, when the patent expires, the innovation becomes freely available, making imitation easier (*disclosure effect*).

We construct three scenarios to investigate the different channels through which patents affect firms' behaviour. In the first scenario, characterized by *full patent protection*, firms immediately and fully patent all the innovations that are eligible. In this scenario a patent affects innovation through the channels highlighted above (protection and disclosure effects): competitors' innovations within the protected interval are blocked, while imitators can freely adopt patented innovations once the patents have expired.

In the second scenario patenting is the outcome of a random process (*probabilistic patent protection*): innovations that are eligible for protection are patented only with a probability Pr_j^p, that is increasing with the incentive to patent, captured by an index I_j^p. The incentive index, in turn, is increasing with the relevance of the innovation and with the strength of protection. This scenario, therefore, is characterized by the the *incentive to patent effect*. We model the probability of patenting as follows:

$$Pr_j^p = \varepsilon^p (1 + I_j^p)^{\zeta^p} \tag{48}$$

where $\varepsilon^p > 0$ is the minimum probability of patenting and $\zeta^p > 0$ affects the "shape" of the function that links the probability of patenting to the incentive index.[28] The incentive index I_j^p is defined as follows:

$$I_j^p = \iota_1 \frac{A_j}{A^{max}} + \iota_2 \tau^l + \iota_3 \tau^b \tag{49}$$

$I_j^p \in (0, 1]$ is a weighted sum of three arguments (closeness to the technological frontier $\frac{A_j}{A^{max}}$, patent length τ^l and patent breadth τ^b) that are crucial in the decision to patent, with weights $\iota_k > 0; k = 1, 2, 3$.[29] In this scenario firms implicitly take into account not only the benefits but also the costs of patenting so that eligible innovations are patented only if the incentive is high enough, depending on the innovation's technological advancement and the regulatory environment.[30]

Finally, the third scenario is a variant of the second one, augmented by the *patent incentive to innovate effect*. We assume that firms increase their innovative effort if they expect greater returns from patenting. Specifically, patenting firms compare the average profits since the beginning of the

[28]Specifically, ζ^p is calibrated to ensure that Pr_j^p remains within the unit interval when I_j^p reaches its maximum value, i.e., $I_{max}^p = 1$. Since we set $\varepsilon^p = 0.1$, the condition $Pr_j^p = 1$ when $I_j^p = 1$ is satisfied if $2^{\zeta^p} = 10$, which implies $\zeta^p = \log_2(10) = 3.3219$.

[29]The weights $\iota_k > 0; k = 1, 2, 3$ are calibrated to guarantee that each of the three terms of the sum in (49) is equal to 1/3 when the arguments attain their maximum values, ensuring $\max(I_j^p) = 1$. Therefore $\iota_1 = 1/3$, $\iota_2 = 1/3\tau_{max}^l$, and $\iota_3 = 1/3\tau_{max}^b$.

[30]According to the empirical evidence there is substantial heterogeneity in the propensity of firms to patent their innovations (Cohen et al., 2000; Hall et al., 2014).

patent's grant with the average profits of non-patenting firms during the same period. If they earn higher profits, patenting firms will increase their R&D intensity σ by 50%.

We assess the effects of patenting by varying the parameters measuring patent length and breadth for each of the three scenarios presented above.[31] We conduct 50 Monte Carlo simulations for each parameter combination and report the mean values and standard deviations for the last 500 time steps. In Figure 9, we present the percentage deviation of GDP under patent protection with respect to the baseline without patents in both three- and two-dimensional plots (left and right columns). In the latter case, we focus on three values for patent length (2, 5, and 20 years).

Our results show that, in the full patent protection scenario (first row of Figure 9), patent length has a clear negative effect on GDP growth, whereas patent breadth does not exert a sizable influence on the results. However, in the presence of the incentive to patent effect (second row), we observe an inverted-U shaped relationship between patent strength and growth for limited patent duration. As τ^b increases, GDP growth first rises and then declines. This effect becomes stronger and more significant when the incentive to innovate channel is active (third row). In the full protection scenario, in fact, all patentable innovations are immediately patented, whereas the incentive to patent effect ensures that the best innovations are patented with a higher probability. This has a dual positive effect: it promotes the diffusion of the best technologies as they become readily available to imitators once their patent expires via disclosure effect, and it also accelerates the diffusion of un-patented innovations via normal imitation activity, thus allowing competitors to get closer to the market leader's technology and potentially leapfrog. Both effects boost growth, provided that the patent duration is not too long. Otherwise, the negative effect of longer protection - by blocking competitors' innovations and delaying the imitation of the best patented innovations - outweighs the positive effect of stronger disclosure, particularly for wider protected areas (high patent breadth).

[31] Specifically, the range of parameter values for length (in quarters) is $\tau^l = \{8, 20, 40, 60, 80, 100\}$, corresponding to a duration ranging from 2 to 25 years. The range of parameter values for breadth is $\tau^b\{0.01, 0.02, 0.05, 0.1, 0.2, 0.5, 0.75, 1, 1.5, 2\}$.

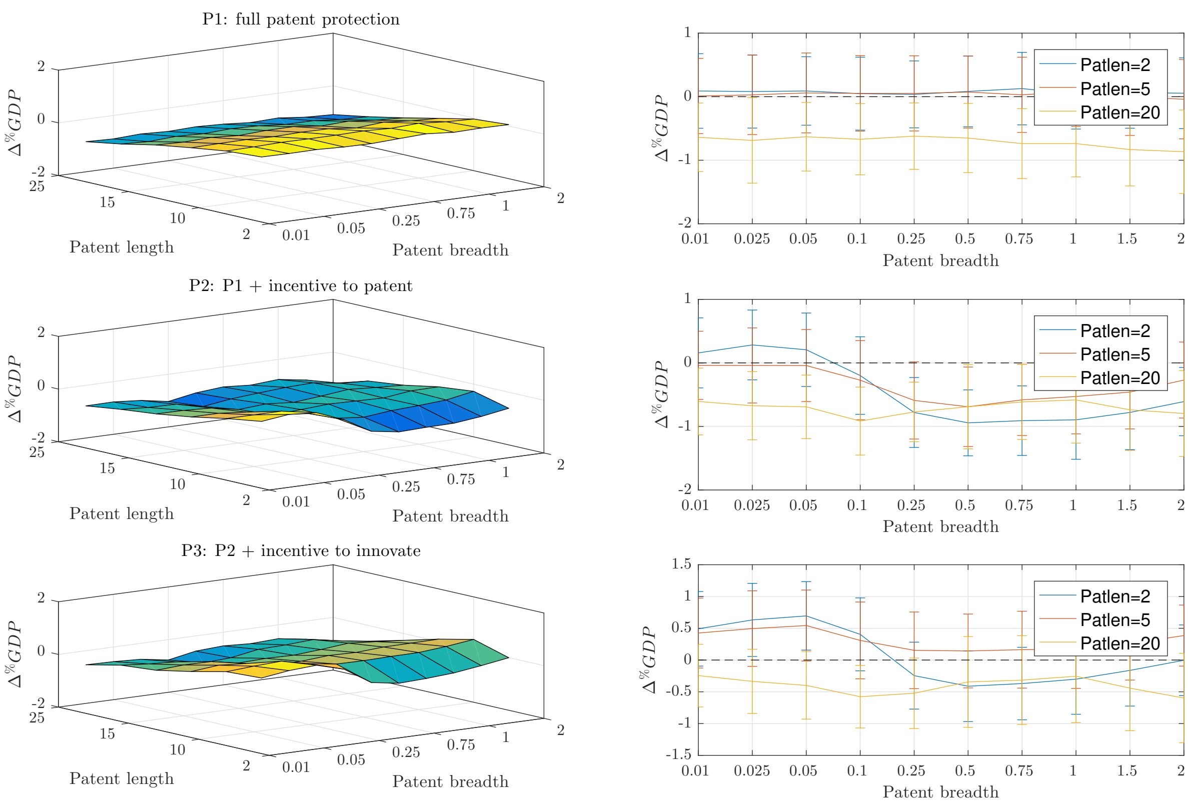


Figure 9: Effects of different patent regimes on GDP growth relative to baseline without patents. Mean and standard deviation from 50 Monte Carlo simulations.

In the third scenario, the patent incentive to innovate effect and the disclosure effect interact positively, leading to a greater positive impact on growth. The incentive effect stimulates the innovating effort of profitable patenting firms, while the disclosure effect promotes the diffusion of the best technologies by making them readily available to imitators once their patents expire. This combination allows better technologies to become available for imitators, resulting in amplified positive effects on growth.

In summary, patents have ambiguous effects on growth, depending on the strength of the patent regime and the type of transmission channels under consideration. When the length and breadth of patents are low, an increase in patent protection has a positive influence on GDP, especially when the best innovations are more likely to be patented (incentive to patent effect) and patenting firms are motivated to increase their innovation effort (patent incentive to innovate effect). Our findings partly contradict those of Dosi et al. (2023c), who find that expanding the coverage and duration of patents has unambiguously negative effects on outcomes. On the other hand, our results are partly in line with Acemoglu and Akcigit (2012), who argue that greater patent protection for technology leaders benefits laggards as well due to positive spillover effects. Our study supports this argument when the incentive to patent and the incentive to innovate effects are at work but only for very limited patent length and breadth. In fact very strong patent protection makes GDP slow down.

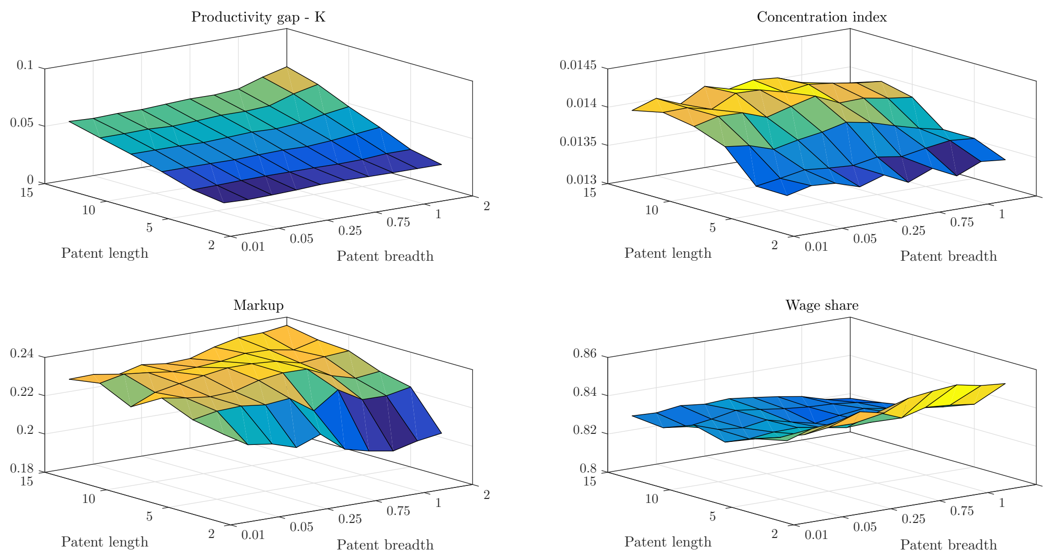


Figure 10: Effects of different patent regimes on productivity gap, market concentration, markup and wage share.

What are the effects of patents on other variables related to declining business dynamism? To answer this question, we examine the impact of stricter patent regimes on productivity gap among capital goods, concentration, average markup, and wage share. The results are presented in Figure 10.[32] We find that stricter patent protection is associated with a wider productivity gap, increasing market concentration and markup, and declining wage share. Therefore, the effects of stronger patent protection are consistent with declining business dynamism, especially when patent length and breadth are sufficiently high.

[32]This experiment is conducted under the standard patent channel assumptions. For robustness, we provide in Appendix C the plots for different patent configurations, but the results are substantially unchanged.

6 Conclusions

In this paper, we have delved into the factors behind the declining business dynamism observed in advanced economies, exploring its macroeconomic and industrial implications. We have employed an extended version of the macroeconomic ABM proposed in Terranova and Turco (2022) to investigate the conditions under which a decrease in knowledge diffusion at the micro level leads to emergent dynamics of declining business dynamism.

We calibrate a baseline scenario with high knowledge diffusion and an alternative scenario characterized by low knowledge diffusion, that differ for the numerical values of key knowledge-related parameters. This procedure allows to replicate by comparison the stylized facts of declining business dynamism. Our simulations reveal that in a low knowledge diffusion environment, the economy displays an increasing tendency towards market concentration driven by widening productivity gaps among firms, then resulting in elevated aggregate markups, decreased labor share, and a decline in both demand and GDP growth. In-depth analyses of firm-level dynamics highlight that, in a context of weak imitation and stringent knowledge constraints, high knowledge-intensive firms are able to exploit their knowledge advantage to adopt best technologies, thus improving productivity and gaining larger market shares vis-à-vis competing firms with limited accumulated knowledge.

We carry out an extensive sensitivity analysis of knowledge-related parameters in the alternative scenario. We find that high knowledge polarization in technology adoption enhances GDP growth under conditions of low knowledge constraints. Conversely, high polarization coupled with high constraints boosts concentration, market power and markups. Our findings suggest that declining business dynamism emerges only when a reduction in knowledge diffusion occurs both in the imitation process among technology producers and in the technology adoption process among technology adopters.

Finally, we introduce a patent system to provide a more tangible interpretation of knowledge diffusion decline and analyze the effects of diverse patent regimes on competition and growth. Our results capture the complex nature of the patents' impact on growth. The effects of patent on macroeconomic performance depend on the strength of patent regimes and the specific transmission channels under consideration. Notably, when patents are characterized by low length and breadth, a stronger patent protection may have positive repercussions on GDP growth, particularly when the best innovations are more likely to be patented (incentive to patent effect) and patenting firms are incentivized to boost innovation efforts (patent incentive to innovate effect). However, excessive patent protection leads to increased concentration and declining output growth.

While our study sheds light on the intricate interplay between knowledge diffusion, technological adoption, and business dynamism, it is not without limitations. Future research could explore alternative model specifications and validate results using alternative methodologies. Further investigation into the drivers of knowledge diffusion reduction, both from a policy and technological perspective, could offer valuable insights into potential intervention points. This could involve examining policies that encourage knowledge-sharing or reduce barriers to innovation diffusion, as well as the role of endogenous entry decisions on competition and economic dynamics. Lastly, the examination of the impact of different patent regimes on various sectors and their implications for innovation, competition, and growth remains a fertile ground for future research.

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Appendix A Calibration and validation of baseline scenario

The parameter values of the model's baseline scenario are outlined in the following Table.

Symbol	Description	Value
W	Number of workers	1000
F_c	Number of C-firms	100
F_k	Number of K-firms	10
Z_c	Number of C-firms visited by each consumer	3
Z_u	Number of firms visited by each unemployed worker	5
Z_{imi}	Number of K-firms visited by each imitator	3
κ	Capital-labor ratio	3
α_w	Elasticity of wage to aggregate productivity	1
$\bar{\iota}$	Long run desired inventories rate	$\frac{3}{17}$
ι	Desired inventories rate	0.3
ρ	Updating coefficient in adaptive expectations of future sales	0.2
$\{c_w, c_f\}$	Marginal propensities to consume out of income	{0.90, 0.60}
c_d	Marginal propensity to consume out of financial wealth	0.05
s_u	Unemployment subsidy replacement rate	0.60
$\{\tau^w,\tau^f\}$	Tax rate on labor and capital income	{0.04, 0.04}
θ	Dividend payout ratio	0.30
δ	Depreciation rate of capital	0.03
δ^{inv}	Depreciation rate of inventories	0.03
δ^z	Depreciation rate of knowledge	0.2
σ	Fraction of retained profits allocated to R&D	0.30
χ	Fraction of R&D expenditure allocated to imitation	0.50
$\{\zeta^{inn}, \zeta^{imi}\}$	Shape of the probability function	{1.8, 1.8}
λ^{imi}	Sensitivity of imitation to technological distance	1
η	Absorptive capacity parameter	1
ψ	Intensity of knowledge spillovers	0.5
β	Intensity of choice of capital goods	0.1
γ	Intensity of knowledge constraints	1
β_s	Intensity of choice of new supplier	1
r	Risk-free rate	0.002
ρ_L	Rate of debt reimbursement	0.05
ε_1	Minimum capital requirement	0.08
ε_2	Maximum exposure to a single borrower	0.25
ν	Memory parameter for long run scale of production	0.85
ε^p	Mimimum probability of patenting	0.1
$(\mu_{FN_1}, \sigma^2_{FN1})$	Folded Normal Distribution parameters for product innovation	(0.03, 0.01)
$(\mu_{FN_2}, \sigma^2_{FN2})$	Folded Normal Distribution parameters for process innovation	(0.005, 0.003)
$(\mu_{FN_3}, \sigma^2_{FN3})$	Folded Normal Distribution parameters for mark-up	(0.03, 0.007)

Table 3: Benchmark parameter setting

The empirical validation of the baseline scenario is performed by running a set of 50 Monte Carlo simulations with different random seeds for 1000 time periods. The artificial time series are constructed by taking averages across simulation runs and then compared with real data. Both simulated and real data are treated with the Hodrick-Prescott (HP) filter in order to isolate the cyclical component from the trend. The observed time series of GDP, consumption, investment and unemployment were downloaded from the FRED database and accounts for quarterly data for the U.S. ranging from Q1 1959 to Q4 1980.

Figure 11 displays the last 100 periods of the cyclical components of the simulated time series for key macroeconomic variables, while figures 12 and 13 compare the auto- and cross-correlation of GDP, consumption, investment and unemployment obtained from simulated data with their empirical counterparts.

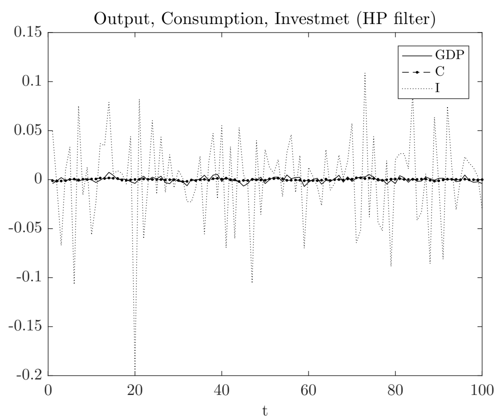

Figure 11: HP-filtered simulated times series for real GDP, consumption, and investment.

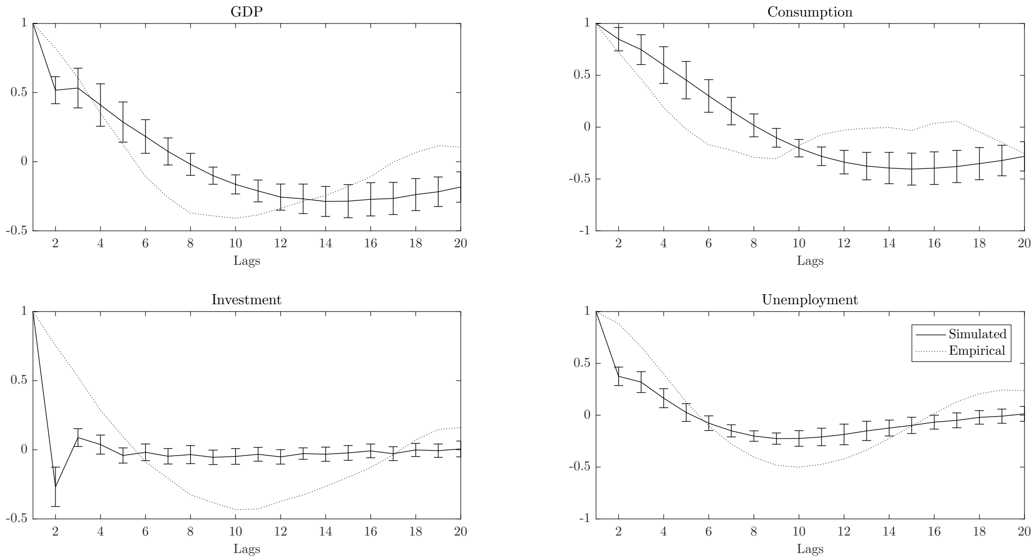

Figure 12: Auto-correlation structure of real GDP, consumption, and investment of simulated and empirical time series.

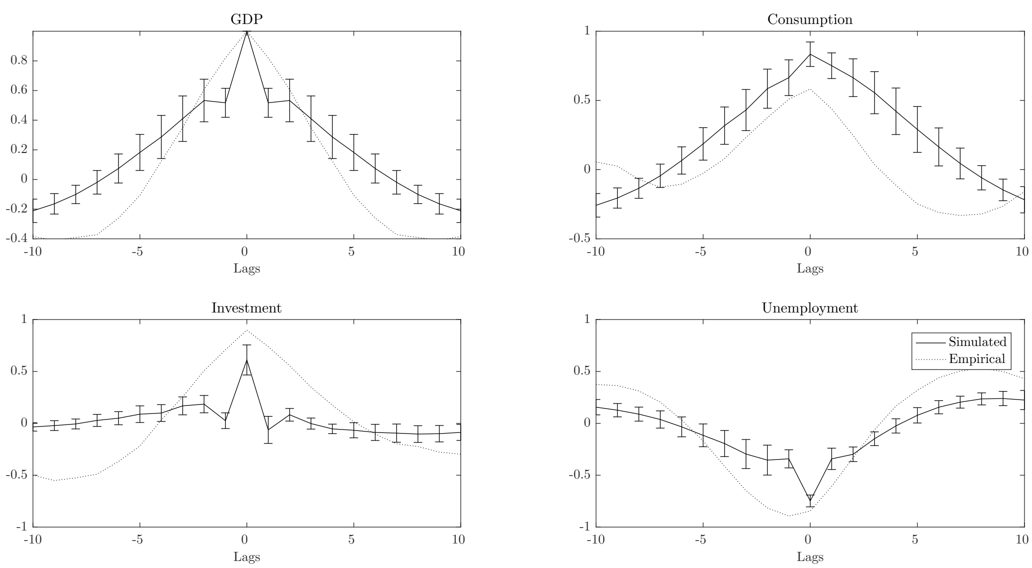

Figure 13: Cross-correlation structure of real GDP, consumption, and investment of simulated and empirical time series.

Appendix B Knowledge gap, effective productivity and capital choice

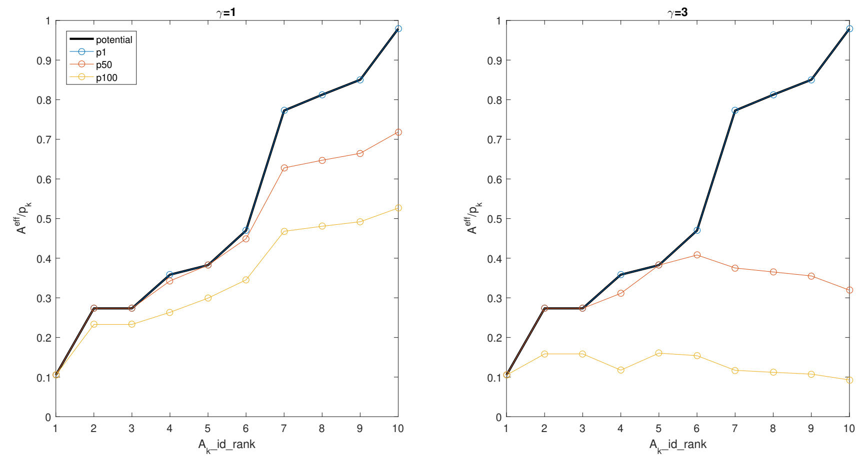

Figure 14: Effective productive-price ratio by capital vintage (sorted in increasing order) for three C-firms representing the top (blue), median (orange) and bottom (yellow) knowledge distribution under two scenarios: low knowledge constraints ($\gamma = 1$, left pane) and high knowledge constraints ($\gamma = 3$, right pane). The black line represents the actual productivity-price ratio of the capital vintages.

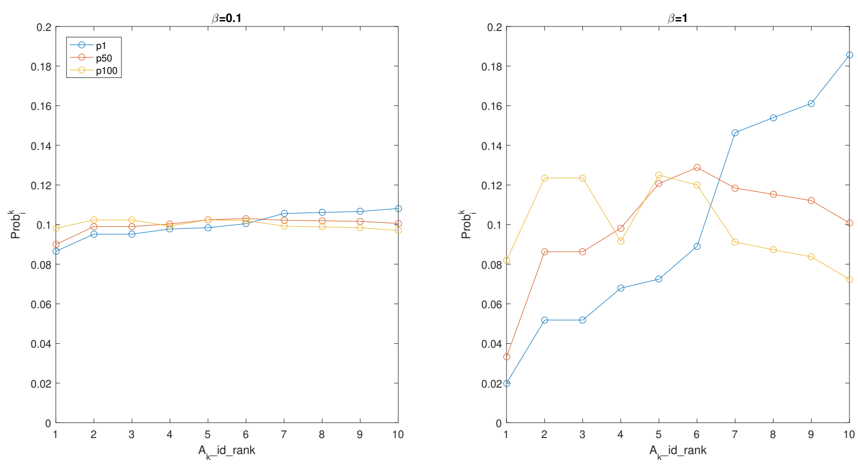

Figure 15: Probability of selecting capital vintage (sorted in increasing order) for three C-firms representing the top (blue), median (orange) and bottom (yellow) knowledge distribution under two scenarios: low knowledge polarization ($\beta = 0.1$, left pane) and high knowledge polarization ($\beta = 1$, right pane).

Appendix C Robustness

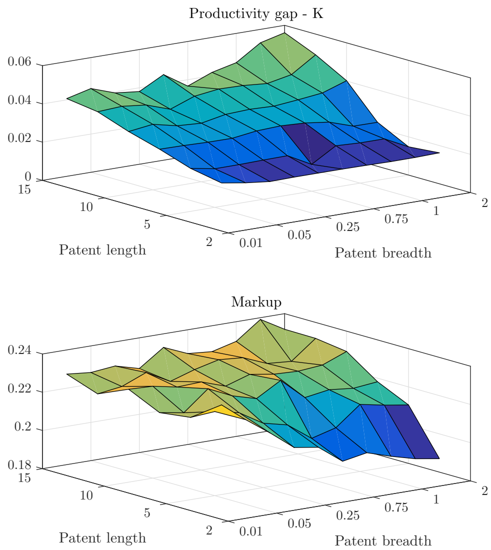

Figure 16: Impacts of patent regimes on key macro variables with incentive to patent effect.

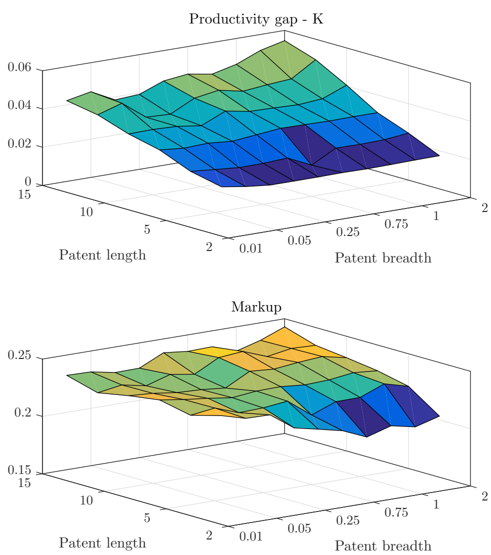

Figure 17: Impacts of patent regimes on key macro variables with incentive to patent + patent incentive to innovate effects.