Industrial Policy in Times of Market Power *

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Abstract

Can standard measures of industrial policy such as R&D subsidies or financial support for machine replacement be effective tools to reverse the current pattern of increasing market power and declining business dynamism? To answer this question we explore the effects of various industrial policy instruments in a macroeconomic agent-based model calibrated to reproduce the decline in US business dynamism over the last half-century. Our results indicate that R&D subsidies alone are insufficient to address the underlying causes of declining dynamism. They become effective, however, when combined in a policy mix with *knowledge diffusion* policies, particularly those favoring advanced technology adoption by small firms. In this case, industrial policy fosters growth by closing the *productivity gap* between leaders and laggards, and thereby curbing market power. These findings suggests a two-pronged approach to the design of industrial policy, integrating firm-level subsidies with knowledge diffusion measures and therefore ensuring that innovation and competition policies advance together.

Keywords: Macroeconomic dynamics, Innovation, Knowledge diffusion, Market power, Industrial policy, Agent-Based Model

JEL codes: C63, E32, L1, L52, O31, O33

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1 Introduction

Once vituperated for its distortionary effects, industrial policy has recently made an impressive come back, in the wake of the structural imbalances generated by the COVID-19 pandemic and rising geopolitical tensions. Recent examples are the Next Generation EU package in the EU, the Inflation Reduction Act (IRA) and the CHIPS Act in the USA. The resurgence of industrial policy occurs in a macroeconomic landscape characterized by the flattening of productivity growth and increasing market power, epitomized by rising concentration and mark-ups and declining labour share (Grullon et al., 2019; De Loecker et al., 2020; Calvino et al., 2020). These features are the hallmark of *declining business dynamism*. The literature so far has focused mainly on the underlying causes of the decline, emphasizing obstacles to *knowledge diffusion* as a key explanatory factor (Akcigit and Ates, 2021, 2023b; Delli Gatti et al., 2023). If we consider potential remedies, a natural candidate comes to mind, namely industrial policy.

Industrial policy primarily seeks to mitigate the *market failure* arising from *innovation as a public good*. Since an innovation can be imitated, firms tend to under-invest in R&D relative to the socially optimal level. This market failure provides a rationale for Pigouvian subsidies targeted at innovating firms or patent protection.[1] Can *standard measures* such as R&D subsidies, financial support for machine replacement or patent protection be *effective tools* to reverse the current pattern of declining business dynamism? This is the *first research question* we ask in this paper.

To answer this question, our starting point is the observation that, while protecting innovators, standard industrial policy may exacerbate another and no less important market failure: the *market power of protected firms*.[2] Such firms can leverage their market position to set prices that generate monopoly profits. In other words, conventional public support for innovation could reinforce the rent-seeking behaviour of protected firms. Moreover, patent protection inhibits, by design, the diffusion of technological knowledge (through imitation) among firms. As mentioned above, obstacles to knowledge diffusion have been pointed at as drivers of declining business dynamism. Hence patent protection is a double edged sword: on one hand, it removes the incentive for firms to under-invest in R&D; on the other hand, it allows technological leaders to strengthen their market power and prevents the diffusion of technological knowledge.

Policy makers thus face a critical *trade-off*: industrial policy aimed at fostering innovation may come into conflict with public policies aimed at enhancing competition and knowledge diffusion. Notably, the current debate on industrial policy in the EU, sparkled by the release of Mario Draghi's report on European competitiveness in September 2024 (Draghi, 2024), seems to overlook this potential trade-off. An emerging "Draghi consensus" seeks to boost the productivity of EU companies by "enabling scale" and supporting corporate consolidation in key sectors. To foster this process,

[1] Of course, there is much more to industrial policy than mitigation of under-investment in R&D. We provide a succinct overview of the recent debate on industrial policy in section 2.

[2] For example, the CHIPS Act extends 6.6 billion dollars in subsidies to TSMC, that already controls roughly 60% of the U.S. semiconductor market.

competition rules and anti-trust enforcement must be substantially watered down.[3]

These consideration bring to the fore the *second research question:* If conventional public support for (or protection of) technological leaders can backfire by increasing their market power, can complementary structural or regulatory measures that enhance knowledge diffusion offset this tendency?

To address these questions, we examine the effects of industrial policy using the macroeconomic agent-based model developed in Terranova and Turco (2022) and Delli Gatti et al. (2023) (henceforth, TTD). In this setting, both producers of machine tools (innovators for short) and producers of consumption goods (entrepreneurs) carry out R&D. By definition, innovators spend in R&D to produce new and more productive vintages of machine tools or to imitate successful innovators. In our setting, however, also entrepreneurs invest in R&D in their role of users of machine tools. In fact, they must accumulate the *technological knowledge* necessary to efficiently operate new and more productive machine tools. The entrepreneurs' access to a high quality vintage of machine tools depends on the *knowledge gap*, i.e., the distance between the technology embodied in the vintage and the adopting firms' knowledge. Firms with low knowledge will not be able to fully exploit the potential productivity of high quality machine tools and therefore they will purchase capital goods of inferior quality. Symmetrically, entrepreneurs endowed with high knowledge will be able to install and efficiently operate high quality machine tools. Heterogeneity in technological knowledge is the source of the *productivity gap* between leaders and laggards in the population of entrepreneurs. Obstacles to knowledge diffusion, both in the adoption process among entrepreneurs and the imitation process among innovators widen the productivity gap, increase market power and ultimately lead to declining business dynamism.[4]

We consider three *categories* of industrial policies: Research Subsidies (RS), which aim to increase R&D spending; Knowledge Diffusion policy (KD) which consist of changes of the institutional framework that aim at facilitating imitation among producers of capital goods or technology adoption by entrepreneurs; Adoption Policy (AP), which provides financial support to entrepreneurs to replace depreciated capital with advanced new machinery. Each category can be further broken down into *instruments* and each instrument can be implemented on its own or in combination with other instruments (*policy mix*) of the same category or of a different category. For each instrument or policy mix, we build a counterfactual scenario and compare the results of simulations against those of a no-policy or baseline scenario calibrated on US data over the interval 1980-2020. The policy instruments we implement in the model are stylized representations of actual measures already implemented or proposed. In the ongoing public debate in the EU and the USA, in fact, transfers to

[3]In the Political guidelines 2024-2029 of the new European Commission, presented to the European Parliament on July 17, 2024, Ursula von der Leyen states "We need a new momentum to complete the Single Market in sectors like services, energy, defence, finance, electronic communications and digital. This will allow our companies – especially our small and medium-sized enterprises – to scale up and make the most of the market. I believe we need a new approach to competition policy, better geared to our common goals and more supportive of companies scaling up in global markets - while always ensuring a level playing field. This should be reflected in the way we assess mergers so that innovation and resilience are fully taken into account."

[4]Kurz (2023) has thoroughly explored the relationship between technological innovation and market power in the presence of intellectual property rights.

firms - such as the Next Generation EU program in Europe and the IRA in the USA - are discussed in parallel with pro-competitive actions to tackle growing market concentration such as the break-up of Big Tech.

Our findings suggest that R&D subsidies alone fail to tackle the underlying causes of declining business dynamism. When targeted to entrepreneurs, research subsidies are ineffective and irrelevant; when targeted to innovators, they have a positive impact on growth but widen the productivity gap and exacerbate the tendency to increasing market power and income inequality. A reversal of this tendency occurs only when R&D subsidies are combined with knowledge diffusion measures that mitigate knowledge constraints for entrepreneurs, thus facilitating the adoption of new technology.[5] Conversely, if intended to promote only imitation, knowledge diffusion measures are neutral at best, and detrimental for business dynamism at worst.

Adoption policy measures yield significant positive effects only when they are knowledge intensive - specifically, when they are combined with a public research infrastructure dedicated to developing and disseminating technological knowledge to support adopting firms. This is not surprising since knowledge-intensive adoption policy simultaneously stimulates investment and foster knowledge diffusion. To the best of our knowledge, our paper is the first one to address the critical two way feedback between market power and industrial policy: on one hand, industrial policy measures affect the market power of firms; on the other hand, the degree of market power makes a significant impact on the transmission and effectiveness of industrial policy.

The paper is organized as follows. Section 2 provides a succinct review of the literature. Section 3 presents and discusses the architecture of the model, with special reference to the main players, entrepreneurs and innovators. Section 4 is devoted to the design of policy experiments. In section 5 we present the empirical validation. In section 6 we illustrate and discuss the results of simulations. Section 7 concludes.

2 Literature review

We position our contribution at the intersection (so far almost an empty set) of two prominent and rapidly expanding strands of literature.

The first strand – mainly empirical in nature – identifies several long-term trends characterizing the decline in business dynamism in advanced economies since the 1980s: (i) increase in market

[5] Greenwald and Stiglitz (2014), p. 45, emphasize the role of knowledge dissemination in the design of industrial policy: "The fact that there are large, persistent differences across countries and firms – at the microeconomic level, large discrepancies between best, average and worst practices – implies that knowledge does not necessarily move smoothly either across borders or over firm boundaries. All of this highlights that one of the objectives of economic policy should be to create economic policies and structures that enhance both learning and learning spillovers." Similarly, Bessen (2022) highlights the need for innovation policy to balance incentives to innovate with mechanisms to encourage knowledge diffusion: "Innovation policy needs to strike a balance between incenting firms to invest in developing new ideas and encouraging the distribution of those innovations and associated knowledge. The evidence of slowing diffusion indicates that the policy framework is out of balance. A policy to encourage diffusion, judiciously applied to preserve innovation incentives where possible, can help restore that balance."

concentration and markups (Syverson, 2019; Grullon et al., 2019; De Loecker et al., 2020; Bajgar et al., 2023); (ii) reduction of the labour share (Autor et al., 2020; Barkai, 2020); (iii) widening productivity gap between leaders and laggards (Akcigit and Ates, 2021, 2023b); (iv) reduction of the entry rate and of the share of young firms (Decker et al., 2016; Calvino and Criscuolo, 2019; Calvino et al., 2020); (v) reduction of productivity growth (Syverson, 2017; Goldin et al., 2024).

The empirical evidence strongly support interdependence among these trends, but few studies have incorporated them in a comprehensive theoretical framework. For instance, Akcigit and Ates (2023b) build an endogenous growth model with firm dynamics to highlight obstacles to knowledge diffusion and increasing market power as key drivers of declining business dynamism. Indeed, evidence indicates that the share of patents held by the top 1% of innovating firms has dramatically increased in the last four decades. Moreover, only a small fraction of predominantly large and already highly productive firms are capable of incorporating advanced technologies in their production processes (Acemoglu et al., 2022; Calvino and Fontanelli, 2023; Cirillo et al., 2023). Along similar conceptual lines, using a macroeconomic agent-based model (ABM) with endogenous technical change and knowledge accumulation, Delli Gatti et al. (2023) explore the conditions under which a reduction in knowledge diffusion leads to declining business dynamism. Only when obstacles to knowledge diffusion affect both imitation of innovative technologies among producers of capital goods and adoption of advanced machine tools on the part of producers of final goods, business dynamism slows down. When knowledge diffusion is limited, the productivity gap between technological leaders and laggards widens. In fact, large knowledge-intensive firms are more likely to adopt cutting-edge technologies, while smaller firms are stuck with less advanced machinery. This leads to a reallocation of market shares toward more productive firms, which ultimately increases their market power and markups. De Ridder (2024) underscores the rise of intangibles inputs, such as software, as a contributing factor to these trends. Firms with a large stock of intangibles benefit from lower marginal costs and higher fixed costs that deter new entrants. In a similar vein, Rikap and Lundvall (2022) and Rikap (2023) examine the process of knowledge generation, diffusion and appropriation in modern economies through the lens of the intellectual monopoly framework (Boldrin and Levine, 2008; Pagano, 2014), particularly within the pharmaceutical, biotech and ICT industries. In line with Florio (2021), they show that technological knowledge, co-produced by a set of actors within innovation systems - such as corporations, start-ups, research institutions, universities -, is ultimately appropriated by large companies through intellectual property rights, leading to oligopoly formation and the extraction of innovation rents.

The second strand focuses on industrial policy, broadly defined as the set of provisions aimed at enhancing the "performance" of non-financial (primarily manufacturing) firms, measured by productivity and growth.[6] Recent advancements have introduced new methods for quantifying industrial

[6] "Any random collection of six economists is sure to produce at least a dozen different opinions on the subject [industrial policy], not least because many economists have trouble in reconciling their gut reaction that industrial policy should not exist with the obvious fact that it does." This quote from Gerosky (1989) illustrates the peculiar place of industrial policy in the literature and in policy making: a lever that is undoubtedly widely used but escapes a shared definition and rationale. See Warwick (2013) for a survey of definitions of industrial policy.

policies across countries and sectors (Criscuolo et al., 2023; Evenett et al., 2024), and for estimating their causal effects (Criscuolo et al., 2019; Juhász et al., 2022), a growing body of literature that is now referred to as the New Economics of Industrial Policy (Juhász et al., 2023). This second strand, too, is primarily empirical, with a strong focus on historical instances of industrial policy (Cimoli et al., 2009), such as trade protection during Napoleonic Wars (Juhász, 2018), the East Asian miracles in countries like China, Taiwan, Korea, Japan and Malaysia (Cherif and Hasanov, 2019; Terzi et al., 2022), and export specialization in Ireland, Spain and Sweden (Anzolin and Benassi, 2024).[7] However, relatively little attention has been paid to the effects of industrial policy in contemporary advanced market economies, where rising market power is concentrated in the hands of large firms and business dynamism is declining.

In the macroeconomic agent-based literature, several studies have examined the economic effects of industrial policy (Dawid and Delli Gatti, 2018). Dawid et al. (2018) use the Eurace@Unibi ABMto investigate the impact of technology-oriented cohesion policies aimed at reducing disparities across sub-national political entities (regions or states) on dualism and the dynamics of income inequality across regions. Their findings suggest that cohesion policies are successful when they provide incentives to firms in lagging regions to adopt the best available capital vintages, thereby facilitating knowledge diffusion across regions. Using a multi-country ABM, Dosi et al. (2021) reach similar conclusions showing that industrial policies can effectively promote international convergence between leading and lagging economies, whereas puremarket-friendly policies or protectionism are insufficient to support the catching-up process. Fanti et al. (2024b) emphasize the role of education and the international trade of capital goods as potential sources of asymmetries across countries, concluding that nurturing internal capabilities through domestic education policies is the most successful path out of a poverty trap. In a recent extension, Fanti et al. (2024a) focus on state-owned enterprises (SOEs) as agents of industrial policy, showing that they can effectively foster productivity and sectoral specialization, supporting convergence in laggard economies.

Focusing on the domestic economy, Dosi et al. (2023) employ the "Schumpeter meeting Keynes" ABM to explore the short- and long-term economic effects of various innovation policies. They compare market-based policies (e.g., R&D subsidies for firms, tax discounts on investment) with direct policies as envisaged in Mazzucato's "Entrepreneurial State" (Mazzucato, 2011), which involve the creation of a public research-oriented producer of advanced capital goods and the establishment of a National Research Laboratory (NRL) dedicated to discovering and disseminating radical innovations. Their results indicate that direct innovation policies lead to higher productivity and GDP growth, especially when combined with the NRL.

While these studies offer valuable insights into the potential benefits and limitations of industrial policies in both domestic economies and international settings, they do not fully consider the specific features of contemporary economies such as rising market concentration, widening productivity gap and declining business dynamism. This oversight could lead to inaccurate estimates of policy effects.

[7] See also Criscuolo et al. (2022) for a review of the evidence in OECD countries.

3 Model setup

The setup we use in this paper is the macro agent-based model extensively discussed in Terranova and Turco (2022) and Delli Gatti et al. (2023) (TTD hereafter). The TTD model builds on the macroeconomic ABM with capital and credit put forward by Assenza et al. (2015) to incorporate technical change and knowledge accumulation. We consider an economy populated by households, firms, the banking system, the Government and the central bank.[8]

The household sector consists of W workers and F firm owners or "capitalists" (one owner per firm). Workers supply labour in-elastically. They can be of two types: *production workers*, employed in the production of goods and *research workers*, i.e., engineers employed in the generation of technical knowledge. If employed, workers earn a wage (uniform across employing firms); if unemployed they get an unemployment subsidy. Firm owners are rentiers, who receive dividends from the firms they own (if after-tax profits are positive). Both workers and firm owners are consumers/savers. 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. Households' savings are accumulated as deposits at the bank.

For simplicity, the banking sector consists of only one bank, that collects deposits from households, extends loans to firms and buys Government bonds. The bank sets the interest rate on loans extended to a given firm by augmenting the risk free rate (set by the central bank) with an external finance premium that is increasing with the firm's leverage.

The Government taxes wages and dividends and provides unemployment subsidies to workers and financial support to firms (as an instrument of industrial policy). Deficits are financed by issuing bonds absorbed by the bank. The central bank sets the risk free rate.

The corporate sector consists of F_k producers of capital goods (K-goods for short) or "machine tools" and F_c producers of consumption goods (C-goods). Producers of C-goods (C-firms) purchase capital goods from producers of K-goods (K-firms) and sell their output to households. K-firms are *innovators* as they generate innovations that are embodied in new and better capital goods. On the other hand, C-firms are *entrepreneurs* as they introduce technical progress into their production process through the purchase of new machine tools.

Productivity improvements of capital goods are brought about by a stochastic innovation/imitation process based on K-firms' expenditure in R&D. Also C-firms perform R&D in order to accumulate *technological knowledge*, which enhances their ability to employ new and better machine tools.

As for the market protocols, workers and firms interact in decentralized labour, credit, consumption, and capital goods markets. The interaction occurs either via the search-and-matching mechanism (Riccetti et al., 2015) or via discrete choice.

[8] In the description of the model, we will focus on firms because they are the main actors in the process of innovation and technology adoption and the recipients of industrial policies. To save on space, we will give only a succinct overview of the rest of the model. Readers are referred to Delli Gatti et al. (2023) for details.

3.1 C-firms

C-firms, indexed with $i = 1, 2, ...F_c$, demand labour, machine tools and credit, and supply C-goods to households. The i-th C-firm sets the desired scale of production $\tilde{Y}_{it}$ on the basis of expected sales Q^e_{it}:

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

where inv_{it-1} are inventories of unsold goods and ιQ^e_{it} are desired inventories, $\iota \in (0, 1)$. The firm's expectation of sales, Q^e_{it}, is determined by a simple adaptive rule based on past forecasting errors with updating coefficient $\rho \in (0, 1)$. In symbols:

$$Q^e_{it} = Q^e_{it-1} + \rho(Q_{it-1} - Q^e_{it-1}) \tag{2}$$

where Q_i represents actual sales. Planned output, therefore, is ultimately driven by past sales.

In order to produce Y_{it}, the firm combines labour N_{it} and the capital stock, consisting of a bundle of heterogeneous capital goods - i.e., machine tools of different "vintages".[9] Denoting with k^v_{it} the units of capital (machine tools) of vintage v, V_{it} the number of vintages of machine tools owned by firm i, A^v_{it} the *actual* productivity of these machine tools, ω^v_{it} the utilization rate, we can define the "average productivity of capital" as follows: $A_{it} := \sum_{v=1}^{V_{it}} x^v_{it} A^v_{it}$ 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 $K_{it} = \sum_{v=1}^{V_{it}} \omega^v_{it} k^v_{it}$. Denoting with B_{it} the productivity of labour, the Leontief production function can be written as follows:

$$Y_{it} = \min\left(A_{it}K_{it}, B_{it}N_{it}\right) \tag{3}$$

From perfect input complementarity follows that the capital-labour ratio is $\kappa = K_{i,t}/N_{i,t} = B_{i,t}/A_{i,t}$. We assume that the capital-labour ratio is constant and uniform across firms. Hence the productivity of labour at firm i is:

$$B_{it} = \kappa A_{it}. \tag{4}$$

This assumption has important implications. The adoption by firm i of a new and more productive technology leads to higher productivity of labour.

To achieve planned production, 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. 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. Given the desired rates of capacity utilization, from the assumption that the capital-labour ratio κ is constant the firm can retrieve labour requirements

[9] Actual output may fall short of planned output due to shortages of productive inputs or of financial resources to purchase them. Moreover, actual sales may be different from actual output: $Q_{it} = \min(Y_{it}, Q^d_{it})$ where Q^d_{it} is actual demand.

(desired employment) $\tilde{N}_{it}$ for the production of goods. If desired employment is greater than the current workforce N_{it-1}, the firm posts vacancies. C-firms need workers also to carry out R&D. Each firm spends RD_{it} to hire research workers. Given the wage rate w_t, therefore, the firm posts vacancies $N_{it}^R = \frac{RD_{it}}{w_t}$. Total vacancies posted by the i-th firm therefore are

$$J_{it} = \max(\tilde{N}_{it} - N_{it-1}, 0) + \mathbb{1}_R \frac{RD_{it}}{w_t} \tag{5}$$

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 a job at the prevailing wage when a match occurs. Therefore firms can reach the desired level of employment only if they are visited by a sufficient number of unemployed workers. 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 labour requirements, i.e., $\tilde{N}_{it} < N_{it-1}$, workers in excess are randomly selected from the firm's workforce and fired.

3.1.1 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 comes from two sources. First, it can be built in-house by spending the budget RD_{it} in R&D (Dosi and Nelson, 2010). Second, it can derive from the knowledge accumulated by other entrepreneurs through *knowledge spillovers*, z_{st}. The law of motion of the i-th firm's knowledge therefore can be written as follows:

$$z_{it} = (1 - \delta^z) z_{it-1} + RD_{it} + a_{it} z_{st} \tag{6}$$

where δ^z is the rate of obsolescence of knowledge and a_{it} is firm's *absorptive capacity*, i.e, the firm's capability to capture knowledge spillovers.

The firm devotes to (in-house) R&D a constant fraction σ of past retained profits π_{it-1}^r: $RD_{it} = \sigma \pi_{it-1}^r$. The knowledge spillover z_{st} is increasing with the competitors' R&D spending: $z_{st} = \psi \sum_{s \neq i} RD_{st}$ where ψ is the spillover intensity. Following the seminal work by Cohen and Levinthal (1989) we assume that past levels of RD_{it} increase the i-th firm's absorptive capacity a_{it}.

We define the *actual* productivity of a capital good of vintage v installed at firm i as follows:

$$A_{it}^v = \begin{cases} A^v & \text{if } \hat{A}^v \leq \hat{z}_{it} \\ \dfrac{2A^v}{1 + e^{\gamma(\hat{A}^v - \hat{z}_{it})}} & \text{if } \hat{z}_{it} < \hat{A}^v. \end{cases} \tag{7}$$

where $\hat{A}^v$ and $\hat{z}_{it}$ are the normalized potential productivity of the machine tool of vintage v and the

normalized firm's stock of technological knowledge.[10]

If technological knowledge is sizable, i.e., $\hat{z}_{it} \geq \hat{A}^v$, actual and potential productivity will coincide. As soon as a *knowledge gap* materializes –i.e., as soon as $\hat{z}_{it}$ falls short of $\hat{A}^v$ – actual productivity falls short of potential productivity. This is key in determining a *productivity gap* among C-firms. Only relatively "large" firms, with high normalized knowledge $\hat{z}_i$ will purchase high productivity machine tools. "Small" firms, characterized by low $\hat{z}_i$ will stick to machine tools of the old vintage. The productivity of the capital stock installed at small firms, therefore, will be lower than that at large firms. From (4) follows that also labour productivity at small firms will be lower than labour productivity at large firms. The parameter $\gamma > 0$ is a measure of the intensity of the *knowledge constraint* on the choice of the capital good: the higher γ, the lower the actual productivity of a given machine tool for each level of technical knowledge. When the constraint on technological knowledge becomes less stringent, the productivity gap shrinks.

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:

$$\mathbb{P}[\text{Firm } i \text{ selects vintage } v] = \frac{\exp\left[\beta(\log A_{it}^v - \log P_t^v)\right]}{\sum_{v=1}^{V} \exp\left[\beta(\log A_{it}^v - \log P_t^v)\right]} \tag{8}$$

where $\beta \in (0, \infty)$ is the *intensity of choice*. Other things being equal, firms with greater accumulated knowledge can extract higher productivity from machine tools of a new vintage and therefore are more likely to purchase them. On the contrary, even if the price were low or financing abundant, firms with low technological knowledge will be unable to exploit machine tools of a new vintage efficiently and therefore they will stick to low quality capital goods. (Dosi and Nelson, 2010).

3.1.2 Prices, profits and net worth

We assume that C-firms set the price by charging a markup μ_{it} on unit labour cost w_t/B_{it}:

$$p_{it} = (1 + \mu_{it})\frac{w_t}{B_{it}}. \tag{9}$$

where w_t is the nominal wage and B_{it} is labour productivity. We assume moreover that the price 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 (4), we can rewrite the pricing rule as follows: $p_{it} = (1 + \mu_{it})\frac{w_t}{\kappa A_{it}}$. The adoption of new and more productive machine tools, therefore, will boost the productivity of labour. We assume that the benefits of technical progress accrue also to workers: the nominal wage evolves over time

[10] Hatted variables are normalized by means of min-max feature scaling. Hence $\hat{z}_i = \frac{z_i - z_{min}}{z_{max} - z_{min}}$ where z_{min} and z_{max} are the lower and upper bound of the ordered set of firms' technological knowledge. Analogously, $\hat{A}^v = \frac{A^v - A_{min}}{A_{max} - A_{min}}$ where A_{min} and A_{max} are the lower and upper bound of the ordered set of vintages' productivity. Of course, normalized variables fall in the unit interval.

at the growth rate of aggregate productivity, measured by the ratio of aggregate GDP Y to total employment N, Unit labour costs at firm i, therefore, will change over time depending on the relative magnitude of the change in labour productivity at the firm level and the change in aggregate labour productivity. If the former grows faster than the latter, unit labour costs will fall and viceversa.

Firms endowed with highly productive machine tools will enjoy high productivity of labour and low unit labour costs. Therefore they can exploit a competitive edge to set relatively low prices and expand their market share at the expense of less productive firms.

3.2 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, one for each K-firm. The quality 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 machine tools of a certain brand, therefore, will be characterized by higher productivity.

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

$$\tilde{Y}_{jt} = Q^e_{jt}(1 + \iota) - inv_{jt-1}, \tag{10}$$

$$Q^e_{jt} = Q^e_{jt-1} + \rho(Q_{jt-1} - Q^e_{jt-1}). \tag{11}$$

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

$$Y_{jt} = B_{jt}N_{jt} \tag{12}$$

where B_{jt} is the productivity of labour.

3.2.1 Innovation and imitation

The j-th K-firm is characterized by a *technological profile* (A^v_{jt}, B_{jt}), consisting of the productivity of the machine tool of vintage v and the productivity of labour. K-firms aim at improving the 'quality' of their profiles by investing a fraction $\sigma \in (0, 1)$ of past retained profits in R&D: $RD_{jt} = \sigma\pi^r_{jt-1}$. The fraction $\chi \in (0, 1)$ of R&D expenditure is allocated to imitation of new technologies generated by other K-firms ($IM_{jt} = \chi RD_{jt}$) while the residual fraction is devoted to in-house generation of new technologies ($IN_{jt} = (1-\chi)RD_{jt}$). In line with the evolutionary literature (Nelson and Winter, 1982; Dosi et al., 2010), 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

$$Pr_{jt}^{inn} = 1 - e^{-\zeta^{inn} IN_{jt}}, \tag{13}$$

$$Pr_{jt}^{imi} = 1 - e^{-\zeta^{imi} IM_{jt}}, \tag{14}$$

where ζ^{inn} and ζ^{imi} are positive parameters. Since ζ^{imi} is uniform across K-firms, we can interpret this parameter as the *degree of knowledge diffusion among K-firms.*

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 evolves as follows

$$A_{jt+1}^{v} = A_{jt}^{v}(1 + \Delta_A), \text{ where} \qquad \Delta_A \sim FN(\mu_{FN_1}, \sigma_{FN_1}^2), \tag{15}$$

$$B_{jt+1} = B_{jt}(1 + \Delta_B), \text{ where} \qquad \Delta_B \sim FN_2(\mu_{FN_2}, \sigma_{FN_2}^2). \tag{16}$$

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 labour 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 pick one of their technological profiles. The probability to imitate a given K-firm is increasing with the parameter λ^{imi}. Finally, firms compare the outcomes from innovation and imitation processes and choose the profile with the highest built-in productivity.

K-firms need workers to carry out both production and R&D activities. The research budget RD_{jt} is used to hire research workers: $N_{jt}^{R} = \frac{RD_{jt}}{w_t}$. As to production workers, based on desired output, the firm has the following labour requirement: $\tilde{N}_{jt} = \frac{\tilde{Y}_{jt}}{B_{jt}}$. Job vacancies are then posted in the labour market:

$$J_{jt} = \max(\tilde{N}_{jt} - N_{jt-1}, 0) + \mathbb{1}_R \frac{RD_{jt}}{w_t} \tag{17}$$

3.2.2 Prices, profits and net worth

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. (2010). Hence, the capital good price is given by

$$p_{jt} = (1 + \bar{\mu}) \frac{w_t}{B_{jt}}, \tag{18}$$

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. Unit labour costs at firm j will go down if labour productivity at the firm level grows faster than aggregate labour productivity.

As in the case of C-firms, profits (or losses) of K-firms are computed as the difference between

production value and total costs. If profits are positive, the K-firm distributes dividends to the owner and retains the residual within the firm. Retained profits are used in part to finance R&D expenditure and in part to accumulate net worth. If the firm experiences a loss, net worth will be reduced correspondingly. Exit through bankruptcy and recapitalization follow the same rules described above for C-firms.

4 Policy experiments: Design

The industrial policy measures under investigation fall into one of three *categories*: Research Subsidies (RS), Knowledge Diffusion policy (KD) and Adoption Policy (AP). RS are transfers to non-financial firms that augment their spending in R&D. KD measures are changes of the institutional setting that spread technical knowledge among firms. AP consists of transfers to small C-firms to facilitate the replacement of depreciated capital with new machines.
In the case of RS and AP, the policy maker is the Government in its capacity of fiscal policy decider. In the case of KD, the policy makers are public authorities in their capacity of regulators or public good providers.

These categories can be broken down into *instruments* or types. RS can be extended to innovators (RS-k) to stimulate innovation/imitation or to entrepreneurs (RS-c) to facilitate technology adoption. Also KD can be of two types. Knowledge Diffusion for K-firms (KD-k) are regulatory changes that make imitation among K-firms easier (e.g., less stringent patent protection) captured by an increase of ζ^{imi}. Knowledge Diffusion for C-firms (KD-c), on the other hand, are institutional or organizational changes that mitigate knowledge constraints in technology adoption among C-firms (e.g., improvements in the educational/training system) captured by a decrease of γ. Finally AP can be of two types: basic (BAP) or knowledge-intensive (KAP). In the latter case, subsidies for machine replacement are coupled with the establishment of a public research infrastructure devoted to developing and disseminating new technical knowledge among adopting firms.

Each instrument can be implemented on its own (*pure instrument*) or in combination with other instruments (*policy mix*) of the same category or of a different category.

4.1 R&D subsidies

RS entails the distribution of public transfers to firms, with different allocations rules and conditionalities. We assume that a fixed public budget TF is allocated to transfers to firms. The budget is computed as a share ρ^{TF} of nominal GDP in 2020, GDP:

$$TF = \rho^{TF} GDP. \tag{19}$$

The duration of the financial support is defined by the parameter τ^{TF} (the calibration of ρ^{TF} and τ^{TF} is outlined in Section 5). Pure RS instruments are perfectly comparable, since they consist in

the allocation of a *given* public budget to transfers to firms. They differ only in the design of the instrument.

When extended to C-firms (RS-c), subsidies enhance the firms' technical knowledge, consequently improving their capacity to identify and adopt the most advanced technologies developed by innovators. Conversely, when targeting K-firms (RS-k), subsidies increases the probability of success in developing new technologies or in imitating technologies developed by competitors.

Once the public budget is determined, the government must decide how to distribute it to firms. Transfers received by firm f (belonging to the set Φ of targeted firms) are $RS_f = s_f TF$. The allocation rule determines the share s_f of the public budget allocated to firm f. The allocation criterion is based on the firm's technological knowledge x_f *relative* to the knowledge accumulated in the business sector to which the firm belongs. In the case of C-firms, $x_f = z_f$, i.e., the allocation criterion is based on the entrepreneur's knowledge. In the case of K-firms, $x_f = A_f$, i.e., the criterion is based on the knowledge embodied in capital goods produced by the innovator. In symbols

$$s_f = \frac{x_f^\alpha}{\sum_{f \in \Phi} x_f^\alpha}$$

We consider three variants of the allocation rule depending on the sign of the parameter α: "picking-the-winner" ($\alpha > 0$); "supporting the laggard" ($\alpha < 0$); uniform allocation ($\alpha = 0$). The first variant aims at bolstering the emergence of leaders by enhancing the technological knowledge of the firms at the top of the ranking in terms of knowledge. The second variant is designed to support followers or laggards in order to squeeze the productivity gap between leaders and laggards. The third rule is neutral since it dictates the uniform allocation of R&D subsidies across firms regardless of their relative knowledge. In the implementation of the policy scenarios, we consider the following numerical values $\alpha = \{-1, 0, 1\}$.

4.2 Adoption Policy

Adoption policy mirrors real-world public interventions that aim at fostering C-firms' investment in new and advanced machinery. For example, in Italy, such policies were introduced in the 1960s ("Legge Sabatini"), and have persisted to date, albeit undergoing occasional updates over time. We explore two types of AP: basic adoption policy (BAP) and knowledge-intensive AP (KAP). We will also consider a policy mix of innovation and adoption subsidies (IAP).

Basic AP Under BAP, the Government allocates public transfers to C-firms to replace depreciated capital with new machine tools of better quality. Implementation occurs in four steps.

First, the Government identifies a subset Φ of firms eligible for AP subsidies. To mimic real world industrial policies - that are frequently designed to support "small" firms - in our setting a firm is AP-eligible if the number of employees is smaller than or equal to the 15-th percentile of

the distribution of firms' workforce. The demand for subsidies of firm $f \in \Phi$ is the value of its *depreciated* capital $\mathcal{K}_f$.

Second, each firm f chooses a specific supplier of machine tools depending on its technological knowledge: applicants with higher knowledge will choose machine tools with higher productivity.

Third, the Government distributes subsidies to eligible firms. The subsidy that firm f receives is:

$$BAP_f = \begin{cases} \mathcal{K}_f & \text{if } \mathcal{K} \leq TF \\ \mathcal{K}_f \frac{TF}{\mathcal{K}} & \text{otherwise.} \end{cases} \tag{20}$$

where $\mathcal{K} = \sum_{f \in \Phi} \mathcal{K}_f$ is the aggregate demand for AP subsidies. In words: If the total demand for subsidies falls short of the predetermined budget TF - defined in (19) - individual demands are satisfied exactly (and actual transfers will be identical to total demand and lower than the predetermined budget). If, on the contrary, the total demand for subsidies is greater than the budget, applicants will be rationed: The Government will extend subsidies to firms ranked in decreasing order of productivity (of the machine tools they want to install) until the budget is exhausted. Firms with low productivity, albeit eligible, may not receive subsidies.

Fourth, firms that received subsidies replace their depreciated capital with new vintages of machine tools.[11] It is worth noting that, under BAP, subsidies serve two simultaneous purposes: to enhance capital productivity for the beneficiaries among C-firms and to stimulate demand for the leading innovators among K-firms.

Knowledge-intensive AP Knowledge-intensive AP is characterized by the integration of AP subsidies, enabling eligible C-firms to replace depreciated capital with new machines, and a Public Research Infrastructure (PRI) dedicated to generating and disseminating technological knowledge.[12]

Under KAP, the budget TF is divided equally between financing basic AP and funding the PRI. We denote with z^{PR} the amount of public funds devoted to the PRI that translates into additional technological knowledge. Hence, the maximum level of technical knowledge available to C-firms, denoted with z^K_{max}, will be the sum of the industry leader's knowledge, z^{Φ}_{max}, and the additional knowledge generated by the public infrastructure. In symbols:

$$z^K_{max} = z^{\Phi}_{max} + z^{PR}. \tag{21}$$

[11] The number of machine tools of vintage v accruing to the eligible firm f under BAP is the ratio of the subsidy (equal to the nominal value of the firm's depreciated capital) to the price of vintage v. The machine tools in question come from the inventory of the K-firm producing vintage v or v-producer. If the inventory is insufficient to meet the demand coming from firm f in the current period, additional units of the vintage will be ordered to the v-producer. Once the replacement of depreciated capital is completed, the subsidy will be transferred to the v-producer.

[12] The European Commission defines Research Infrastructures as "facilities that provide resources and services for research communities to conduct research and foster innovation." Florio and Sirtori (2016) conducted a social cost-benefit analysis, documenting the positive effects of large-scale, capital-intensive research infrastructures in Europe. These impacts include knowledge production, technological spillovers, human capital development, broader cultural effects, services to third parties, and non-use benefits. Additionally, Florio (2021) puts forward proposals addressing three major long-term challenges for European research infrastructures: health risks, climate change, and Big Data governance.

Under KAP, in addition to receiving subsidies to modernize its capital stock, each eligible C-firm benefits from a *knowledge transfer* from the PRI so that the new knowledge available to firm f, denoted with z'_f will be generally higher than before. In our setting, the new knowledge is drawn from a uniform distribution with a lower bound at the firm's current level of technical knowledge, z_f, and an upper bound at z^K_{max}. In symbols:

$$z'_f \sim \mathrm{U}(z_f, z^K_{max}) \tag{22}$$

The eligible C-firm will then choose the vintage of machine tools to replace its depreciated capital, compatible with the newly acquired knowledge. Additionally, the knowledge constraint parameter γ is reduced from 5 to 1 under this policy, reflecting a high level of knowledge diffusion during the adoption process.

We have also built a policy mix (Innovation AP or IAP) blending KAP with a research subsidy (RS-k) for innovators, extended for 20 periods, i.e., 5 years.

4.3 Knowledge diffusion policies

Knowledge Diffusion policies are captured by changes in two knowledge-related parameters. Under KD-k, the imitation capacity parameter increases and is set at $\zeta^{imi} = 1.8$, making it easier for K-firms to imitate competitors' technologies. Under KD-c, the knowledge constraint parameter decreases to $\gamma = 1$, making it easier for C-firms to adopt more advanced technologies. The new values of these parameters are chosen in order to replicate the pre-1980 macroeconomic landscape in the US.

Par	Description	Baseline	
		Pre-1980	Post-1980
λ^{imi}	Sensitivity of imitation to technological distance	1	5
ζ^{imi}	Imitation capacity	1.8	0.01
β	Intensity of choice of K-goods	0.1	1
γ	Intensity of knowledge constraints	1	3

Table 1: Knowledge-related parameters for the baseline scenario pre- and post-1980.

5 Empirical validation and simulation set-up

Following Delli Gatti et al. (2023), we calibrate the model to replicate key stylized facts of the U.S. economy from 1950 to 2020, focusing on GDP growth, market concentration, markups, and the wage share.[13] The numerical values of the parameters are initially set to match U.S. quarterly macroeconomic data for 1950-1980. To calibrate the macroeconomic environment of 1980–2020,

[13]For a detailed description of the calibration procedure, see Delli Gatti et al. (2023).

marked by increasing market power, we then adjust only four parameters, that capture the role of knowledge diffusion both in technology imitation among K-firms and technology adoption among C-firms. This adjustment aims at replicating the landscape of low knowledge diffusion typical of the US economy in the 1980-2020 time span and therefore consists in: (i) a reduction in K-firms' imitation capacity ζ^{imi}, (ii) an increase in the sensitivity to technological distance for imitating firms λ^{imi}, (iii) an increase of the intensity of choice for capital goods β, reflecting greater knowledge polarization among C-firms, and (iv) an increase in the knowledge constraint intensity γ. Table 1 shows the numerical values of these knowledge-related parameters for the two phases of the baseline scenario. The full parameter configuration is shown in the Appendix (Table 4).

The baseline scenario calibrated on data for the 1980-2020 time span serves as a benchmark for evaluating policies within a context of increasing market power and declining business dynamism. Table 2 summarises the model's empirical validation, comparing simulated outcomes with empirical data for four key variables.

Variable (%)	Empirical			Simulated			No policy	
	1980-90	2010-20	Δ	1980-90	2010-20	Δ	2020-60	Δ
GDP growth	3.80	2.65	-1.15	3.9	2.3	-1.6	2.39	0.09
Concentration	38	43.5	5.5	8.06	18.22	10.16	23.26	5.04
Markup	1.2	1.61	0.41	1.34	1.49	0.25	1.61	0.12
Labour share	75.36	70.9	-4.46	77.79	73.41	-4.38	71.16	-2.26

Table 2: Comparison of empirical evidence and results of simulations for key variables, 1980–2020. Market concentration is measured by the market share of the 4 largest firms (CR4 index). Sources of empirical data: FRED database (GDP growth), Autor et al. (2020) (concentration), De Loecker et al. (2020) (markup), Guerriero (2019) (labour share).

The model successfully replicates key macroeconomic indicators, such as GDP growth, average markup, and labor share, both in levels and absolute changes. However, it underestimates concentration levels, a limitation arising from the assumption of a constant number of firms in the model. Despite this shortfall, the model reasonably captures the magnitude of changes observed in empirical data before and after 1980.

The last column presents simulated data for the baseline scenario without industrial policy over the period 2020-2060. As shown in the table, this scenario maintains a relatively stable GDP growth rate, while business dynamism indicators mirror the post-1980 U.S. landscape: widening productivity gaps, rising concentration, higher markups, and a declining labor share. In the absence of policy intervention, these trends point to a continued tendency of rising market power and declining business dynamism in the future.

Figure 1 illustrates the simulated evolution of key variables under the baseline scenario for the period 1980-2060. This scenario is characterized by a widening productivity gap across C-firms, as knowledge-intensive firms tend to adopt more advanced machinery, achieving faster productivity gains compared to low-knowledge intensive firms. As the productivity gap grows, technological

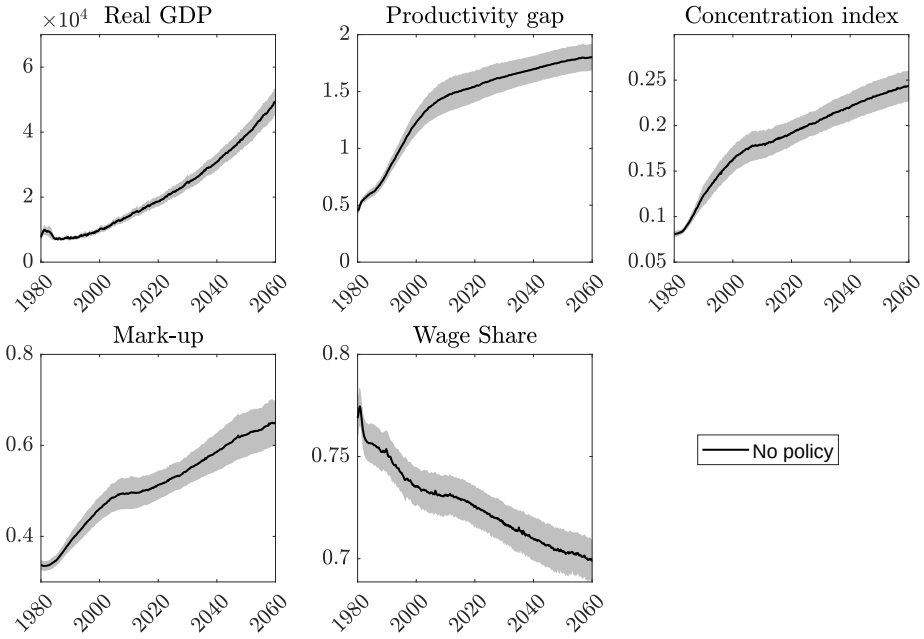


Figure 1: **Evolution of key economic variables under the baseline scenario**
The productivity gap is measured by the coefficient of variation of the distribution of labour productivity of C-firms. Market concentration is measured by the market share of the four largest C-firms. Black lines represent the mean of 100 Montecarlo simulations. Confidence bands in grey.

leaders become "superstars", expanding their market shares and driving up the concentration index. These dominant firms are then able to increase their markups without losing competitiveness, which in turn leads to a decline in the labour share of income.

6 Policy experiments: Results

We evaluate the impact of various industrial policy measures over the period 2020–2060 by comparing simulation outcomes of the counterfactual scenarios generated by such policies with the baseline scenario without policy. We build each counterfactual scenario assuming that a given policy is implemented in 2020 and remains in effect for a specified duration, either temporary (τ^{TF}=20 quarters, or 5 years) or permanent. In the simulations, we set $\rho^{TF} = 0.07$, which aligns with the U.S. public R&D funding to GDP in 2020 and the outlays required for the 2022 IRA package (Akcigit and Ates, 2023a).

Our policy experiments are structured as follows. First, we examine the effects of R&D subsidies (RS) both as a standalone policy instrument and as part of a broader policy mix, specifically in combination with Knowledge Diffusion (KD) policies. Second, we explore the effects of adoption policies (AP) designed to more realistically integrate the key features of both subsidies and knowledge diffusion measures.

6.1 R&D subsidies

Label	Policy	Parameters	Description
RS-c0	Pure RS-c	-	R&D subsidy to C-firms only
RS-c1	RS-c + KD-k	$\uparrow \zeta^{imi}$	Increased imitation
RS-c2	RS-c + KD-c	$\downarrow \gamma$	Reduced knowledge barriers for adoption
RS-c3	RS-c + KD-k + KD-c	$\uparrow \zeta^{imi}, \downarrow \gamma$	Combined effects
RS-k0	Pure RS-k	-	R&D subsidy to K-firms only
RS-k1	RS-k + KD-k	$\uparrow \zeta^{imi}$	Increased imitation
RS-k2	RS-k + KD-c	$\downarrow \gamma$	Reduced knowledge barriers for adoption
RS-k3	RS-k + KD-k + KD-c	$\uparrow \zeta^{imi}, \downarrow \gamma$	Combined effects

Table 3: Industrial policy experiments based on Research Subsidies and Knowledge Diffusion measures

In the first policy experiment, R&D subsidies are distributed either to innovators (K-firms) or entrepreneurs (C-firms) according to the uniform allocation rule (all the targeted firms receive the same subsidy) for 5 years.[14]. KD policies are characterized by a permanent change of one or both the key imitation and adoption parameters.

[14]In other words, in these experiments we set $\alpha = 0$ and $\tau^{IP} = 20$. We defer the analysis of the effects of non-neutral allocation rules to Appendix B.1.

Table 3 lists the first round of policy experiments. RS extended to entrepreneurs (scenario RS-c0) allow C-firms to accelerate knowledge accumulation; RS extended to innovators (RS-k0) allow K-firms to achieve a higher probability of innovation and imitation. Policy mixes RS-c1 and RS-k1 combine subsidies to C-firms and K-firms respectively with measures that facilitate imitation among K-firms (increase of ζ^{imi}). Policy mixes RS-c2 and RS-k2 combine subsidies with measures that soften knowledge constraints in technology adoption on C-firms (reduction of γ). Finally, policy mixes RS-c3 and RS-k3 combine subsidies with measures that facilitate imitation among K-firms and mitigate knowledge constraints on C-firms (increase of ζ^{imi} and reduction of γ).

We analyze the results of simulations in three steps. First, we assess the *macroeconomic effects* of policies, focusing on GDP and other aggregate indicators. Second, we evaluate the *cross-sectional effects* focusing on the statistical distributions of three key features of C-firms: labour productivity (C-productivity for short), market share and markup. Finally we assess the effects of policies on the estimated *density functions* (at the end of the simulation period) of C-productivity and of the productivity of machine tools (K-productivity for short). At the end of each step, we summarize the findings in numbered Results.

Macroeconomic effects Figure 2 shows the effects of R&D subsidies targeting entrepreneurs (RS-c) – either as a standalone policy or in combination with KD measures – on real GDP and four business dynamism indicators: the productivity gap, measured by the coefficient of variation of the distribution of labour productivity of C-firms; market concentration, measured by the market share of the four largest C-firms; the weighted-average mark-up and the labour share of GDP. We run 100 Monte Carlo simulations for each scenario and compute the mean. Each line represents the mean percent deviation from the baseline of each variable under the policy scenario. Figure 3 depicts the dynamics of the same variables under R&D subsidies targeting the innovators (RS-k).[15]

From the top left panel of figure 2 we observe that research subsidies to entrepreneurs alone (RS-c0) have essentially no effect on GDP or other indicators of business dynamism. When RS-c is combined with policies aimed at improving knowledge diffusion, the results change in an interesting way. First, real GDP increases in all scenarios characterized by a policy mix. When RS-c is paired with policies facilitating imitation by K-firms (RS-c1, blue) - without addressing knowledge constraints among adopting firms - the trend of increasing market power intensifies: the productivity gap, concentration and mark-up rise *more* than in the baseline, while the wage share declines *more* sharply. In essence, the combination of research subsidies to entrepreneurs and pro-imitation measures *exacerbate* the tendency toward increasing market power characterizing the baseline scenario. In contrast, the combination of RS-c with measures promoting technology adoption by C-firms (RS-c2, green) reverses the trend of increasing market power. In this scenario, the productivity gap narrows alongside falling concentration and markups, with the wage share rising.
We also consider a policy mix of RS-c with KD measures facilitating both adoption and imitation

[15]Figure 14 and 15 in Appendix B.2 display the same variables in absolute terms, rather than percentage changes, to provide additional insights into the evolution of key variables over time.

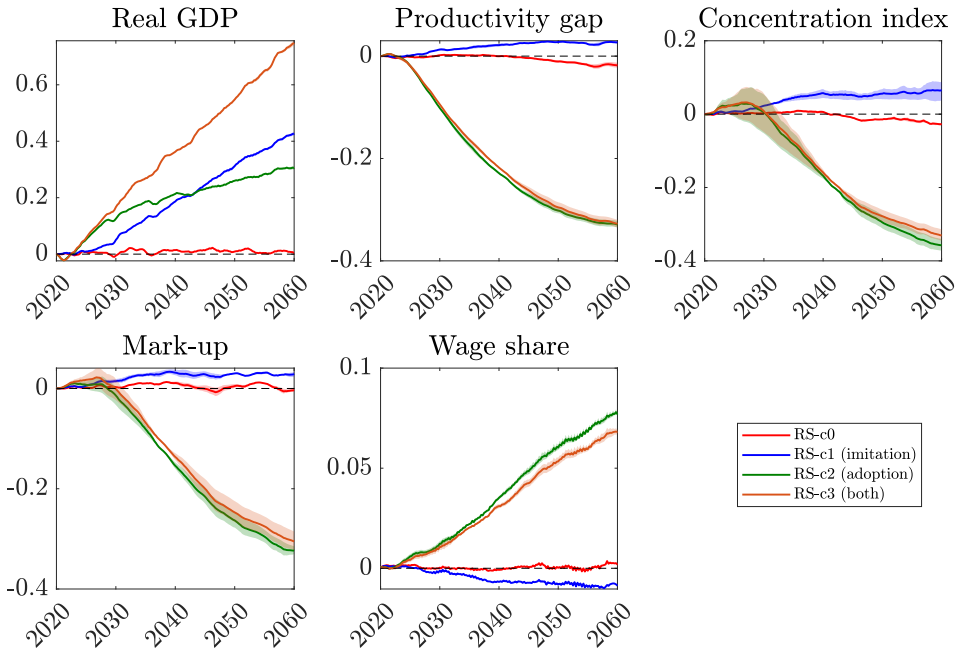


Figure 2: **Macroeconomic effects of R&D Subsidies for C-firms.** Policy scenarios: (i) RS-c0 (red); (ii) policy mix of RS-c and Knowledge Diffusion via Imitation (RS-c1, blue); (iii) policy mix of RS-c and Knowledge Diffusion via Adoption (RS-c2, green); (iv) policy mix of RS-c and combined Knowledge Diffusion policies via Imitation and Adoption (RS-c3, orange). Solid lines represent the mean across 100 MC simulations; shaded areas represent 95% confidence intervals.

(RS-c3, orange). The business dynamics in this scenario are similar to the green scenario, with higher GDP growth, although concentration and mark-ups decline slightly more under RS-c2.

Figure 3 presents results for the the policy of R&D subsidies targeting K-firms. The top left panel shows that RS-k0 alone (red) has a substantial positive effect on GDP, unlike the pure RS-c0 policy. Even without complementary measures, subsidizing the research activities of innovators significantly boosts economic growth. However, RS-k0 on its own does not significantly alter business dynamism indicators and is unable to revert the trend of increasing market power.

Similarly to the RS-c experiment, combining R&D subsidies for K-firms with knowledge diffusion measures substantially amplifies their impact on GDP. Real GDP growth increases across all scenarios characterized by a RS-k and KD policy mix. When RS-k is paired with pro-imitation measures for K-firms (RS-k1, blue), the productivity gap, the concentration ratio and the average mark up rise *more* than in the baseline and the labour share declines *further*. On the contrary, the combination of RS-k with pro-adoption measures (RS-k2, in green) is capable of reversing the trend of increasing market power, leading to a decline in the productivity gap, market concentration, and markups, alongside a rise in the wage share. The policy mix of RS-k with KD policies supporting

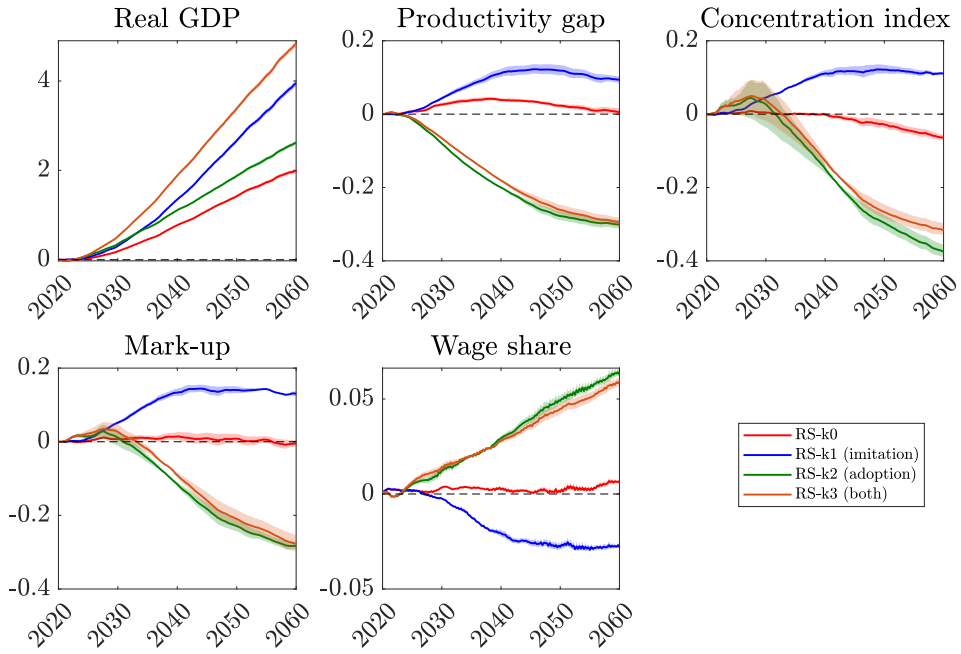


Figure 3: **Macroeconomic effects of Research Subsidies for K-firms.** Policy scenarios: (i) RS-k0 (red); (ii) policy mix of RS-k and Knowledge Diffusion via Imitation (RS-k1, blue); (iii) policy mix of RS-k and Knowledge Diffusion via Adoption (RS-k2, green); (iv) policy mix of RS-k and combined Knowledge Diffusion policies via Imitation and Adoption (RS-k3, orange). Solid lines represent the mean across 100 MC simulations; shaded areas represent 95% confidence intervals.

both adoption and imitation (RS-k3, orange) yields results similar to the green scenario.

We summarize the macroeconomic effects of RS in the following:

Result 1. ***R&D subsidies: Macroeconomic effects*** *Pure research subsidies targeted at entrepreneurs (RS-c0) have no effect on GDP, while those targeted at innovators (RS-k0) significantly boost GDP. However, pure RS policies, regardless of the targeted firms, do not alter the trend of increasing market power seen in the no-policy scenario.*
A policy mix of RS with measures promoting imitation among K-firms (RS-c1, RS-k1) leads to faster GDP growth compared to the baseline, but tends to exacerbate the increase in market power.
Only when RS are blended with measures promoting technology adoption by C-firms (RS-c2 and RS-k2) we observe both faster GDP growth and a reversal of the trend towards increasing market power: the productivity gap, concentration and the mark up decrease and the wage share rises.

Figure 4 presents the boxplots of GDP growth, concentration, market power and labour share at the end of the simulation period (2060) in the baseline scenario (no-policy) and in all the policy scenarios considered so far. Results inferred from Figures 2 and 3 are confirmed. The policy mix

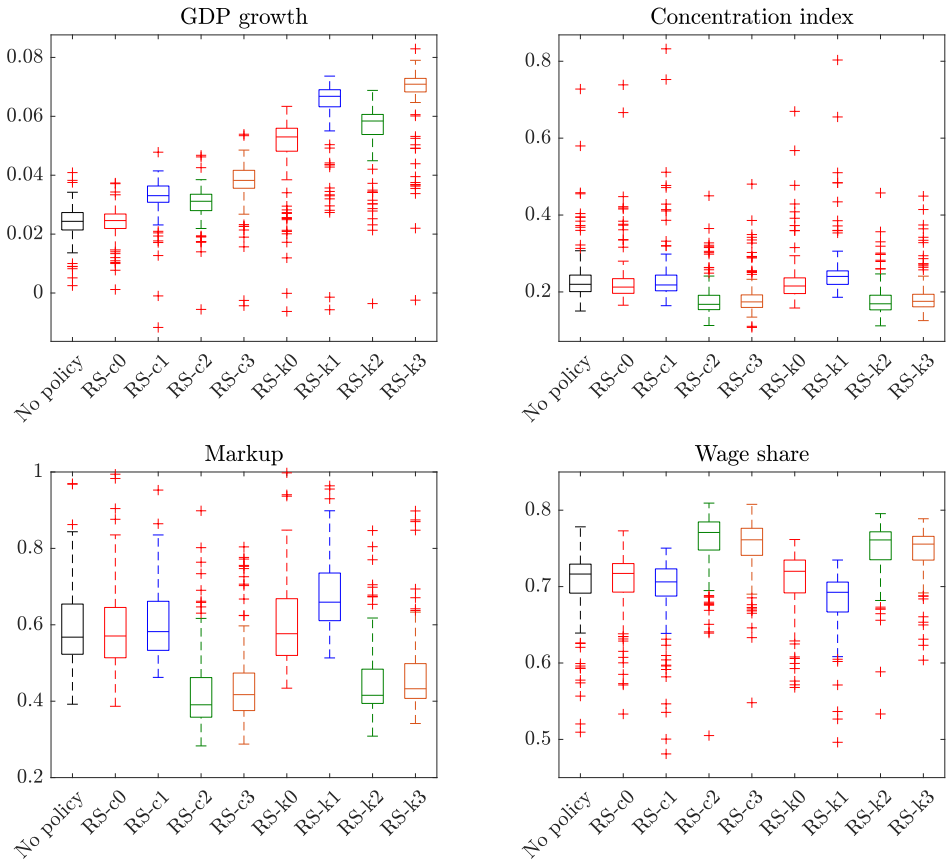


Figure 4: Boxplot of GDP growth, market concentration, markup, and wage share in the year 2060, based on 100 Monte Carlo simulations under the industrial policy scenarios listed in Table 3.

that achieves the highest GDP growth and the lowest market power consists of research subsidies to innovators combined with measures promoting knowledge diffusion in both the C-sector and K-sector (RS-k3). In this scenario, K-firms become more innovative due to public R&D support, leading to higher-quality capital vintages. Additionally, competitors can easily imitate innovations and C-firms can easily adopt high quality machines. This accelerated technology diffusion helps laggardsin the C-sector to catch up with industry leaders, making the productivity gap shrink.

Cross-sectional effects To further explore the mechanisms driving the transmission of industrial policies, we analyze cross-sectional evidence from the simulations. Each panel of Figure 5 presents the growth rates (over the interval 2020-2060) of three key characteristics of C-firms (labor productivity, market share, and markup) across different percentiles of the distribution of labour productivity. The x-axis displays the 20th, 40th, 60th, 80th, and 100th percentiles in 2020, ensuring that we assess

the growth rates for the same firms across these variables.[16] For simplicity and lack of a better term, we refer to firms in the 20th, 40th, and 60th percentiles as *small* firms while firms in the 80th and 100th percentiles will be labelled *large* firms.

We plot the evolution of each characteristic for the baseline and all the policy scenarios. An upward trend indicates *increasing polarization* or cross-sectional divergence, because small firms (in 2020) fall behind large firms over time. Conversely, a downward trend suggests decreasing polarization or convergence. The top row of Figure 5 illustrates the effects of research subsidies to entrepreneurs while the bottom row shows the impact of research subsidies to innovators. In both cases we consider RS either as a pure instrument or in combination with KD policies.

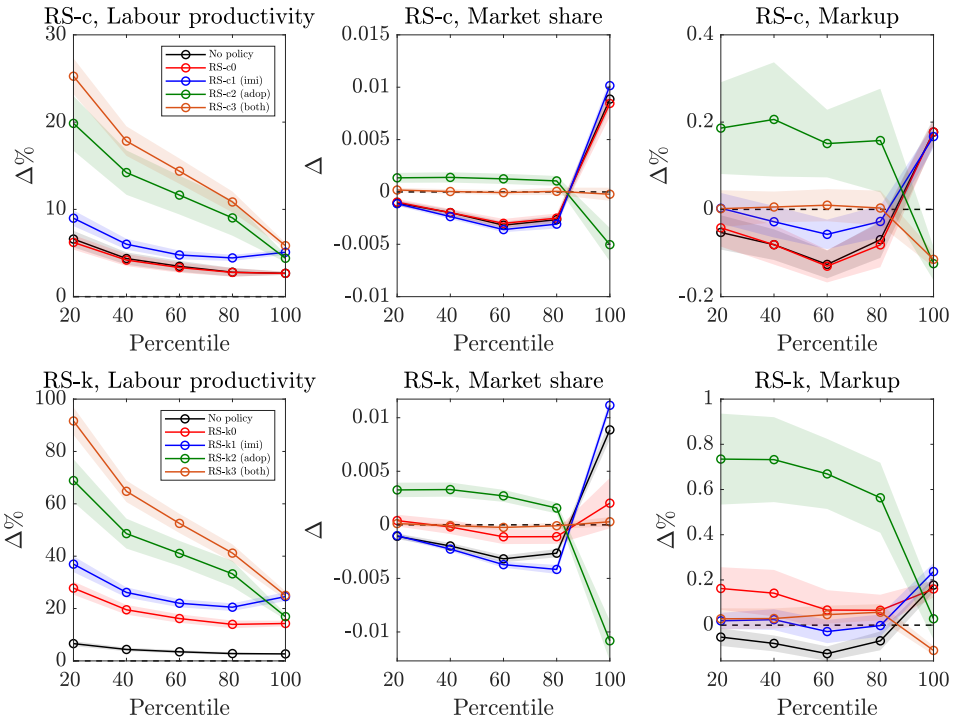


Figure 5: **Cross-sectional effects of RS policy** Growth rate of labour productivity, market share and mark up across percentiles of the distribution of C-firms under RS policy experiments: (i) No-policy (black); (ii) pure RS (red); (iii) policy mix of RS and Knowledge Diffusion via Imitation (blue); (iv) policy mix of RS and Knowledge Diffusion via Adoption (green); (v) policy mix of RS and combined Knowledge Diffusion policies via Imitation and Adoption (orange). Solid lines represent the mean across 100 MC simulations; shaded areas represent 95% confidence intervals.

Let's start from the no-policy scenario (black line). In this case, the rate of growth of labour productivity (left panel) slightly decreases across percentiles, denoting a mild tendency to conver-

[16]There are 100 C-firms. Each percentile score corresponds to a specific firm ID positioned at that percentile of the productivity distribution in 2020.

gence. In contrast, the rates of change of the market share and of the mark up (middle and right panel) are U-shaped: They are negative and decreasing for small firms, increase and turn positive for large firms. This pattern suggests *increasing polarization of market power*: firms with low (high) market power (measured by market share and mark up) - will experience a reduction (increase) of the latter.

Let's start from R&D subsidies extended to entrepreneurs (top row). RS-c0 (red line) has no effect on firms dynamics, as the red line overlaps closely with the baseline (black line) across all percentiles. When combined with pro-imitation measures (RS-c1, blue), the growth rate of productivity shifts up for any percentile. Under the policy mix of RS-c and pro-adoption measures (RS-c2, green), productivity growth is inversely correlated with firm size, narrowing the gap between leaders and laggards. Market share and markups follow opposite trends, increasing under RS-c1 and decreasing under RS-c2. Thus, the polarization of market power increases under RS-c1 and decrease under RS-c2. The results for RS-c3 (orange), which combines both adoption and imitation measures, are broadly consistent with those of RS-c2 in terms of labor productivity. However, under RS-c3, market share growth remains uniform and close to zero.

Now, let's explore the cross-sectional effects of subsidies extended to innovators (bottom row). Research subsidies to K-firms alone (RS-k0, red) significantly boost productivity growth across all firm sizes. Similar to the RS-c experiment, productivity growth is enhanced across all policy mixes involving RS-k and KD compared to RS-k0. When RS-k is combined with pro-imitation measures (RS-k1, blue), productivity growth increases but remains relatively stable across percentiles. When RS-k is combined with pro-adoption measures (RS-k2, green), instead, productivity growth far exceeds the baseline and declines with firm size. Market share and markups also decrease with firm size, indicating a trend toward *convergence*: firms with low (high) market power will experience an increase (reduction) of the latter.
The policy mix of RS-k and KD measures (RS-k3, orange) yields even greater productivity growth. However, unlike RS-k2, market share and markups grow uniformly across firms in RS-k3.

Interestingly, small firms obtain the largest gains in market power under RS-k2 (green), despite the largest gains in productivity occurring under RS-k3 (orange). This puzzle can be explained by examining the variation in markup at the top of the distribution. Under RS-k3, large firms respond to the competitive threats posed by small and highly productive firms by strategically reducing their markup to preserve market share. Conversely, under RS-k2, where productivity gains are slightly lower, large firms do not react as firmly, allowing small firms to take advantage of the situation and expand their market shares and markups.

We summarize these considerations in the following:

Result 2. ***R&D subsidies: Cross-sectional effects*** *When research subsidies are directed at entrepreneurs (RS-c0), they have no impact on productivity growth. On the contrary, if targeted at innovators (RS-k0), they lead to significant productivity gains. In both cases, pure RS policies do not mitigate the increasing polarization of market power observed under the no-policy scenario. Policy*

mixes combining RS with measures to promote imitation among K-firms (RS-c1, RS-k1) exacerbate this polarization of market power. Only when RS policies are combined with measures supporting technology adoption by C-firms (RS-c2, RS-k2) is the trend toward increasing productivity gaps and market power polarization reversed.

Density functions To gain further insights from the micro-level dynamics, Figure 6 shows the estimated density functions of the productivity of capital goods (K-productivity; left column) and of the productivity of labour at C-firms (C-productivity, right column) in 2060 under the baseline (top row) and in all the policy scenarios when subsidies are targeted to entrepreneurs (RS-c). Analogously, Figure 7 illustrates the same productivity distributions when subsidies are targeted to innovators (RS-k). The *shape* of the density function helps to understand the interplay between the distribution of machine tools of heterogeneous quality and the distribution of adopting firms characterized by heterogeneous labour productivity.

In all scenarios, the density functions exhibit a multi-modal structure. Starting from the baseline scenario (first row, black), in the absence of policy, the K-productivity density function (top left) is clearly bimodal, with the probability mass concentrated around two distinct levels: a minor mode at approximately 10 and a major mode at around 75.[17] On the right, the distribution of C-productivity mirrors that of K-productivity. Most C-firms are clustered around a major mode at approximately 25, representing the laggards, while a smaller group is clustered around a minor mode at 75, representing the leaders. This configuration of the density function, that we refer to as ML-FH (Many with Low productivity, Few with High productivity), highlights the significant productivity gap between entrepreneurs. The *amplitude* of the bimodal density function - the difference between the major and minor modes - serves as an alternative measure of the productivity gap.
Comparing the K- and C- distributions we can draw the conclusion that many laggard firms are utilizing the few low-productivity machine tools, while a few leader firms are benefiting from the many high-productivity machine tools.

From visual inspection of the second row of Figure 6 we conclude that a policy of pure R&D subsidies targeted at entrepreneurs (RS-c0, red), does not alter the position or shape of the density functions. Under RS-c1 (third row, blue), the density functions shift to the right compared to the baseline preserving the same configurations. Facilitating technology imitation among K-firms significantly enhances the average quality of capital goods and the average productivity of C-firms. However, similar to the baseline, only few highly productive C-firms gain access to the best technologies, as laggards continue to face knowledge constraints which force them to adopt less productive machine tools.
Notably, the amplitude of the density of C-productivity is larger under RS-c1 than in the baseline, indicating a greater productivity distance between leaders and laggards. This is the reason why, as shown in Figure 2, the policy mix RS-c1 leads to higher GDP growth but does not modify the

[17]The minor (major) mode is the value in the support of the distribution associated with the lower (higher) peak.

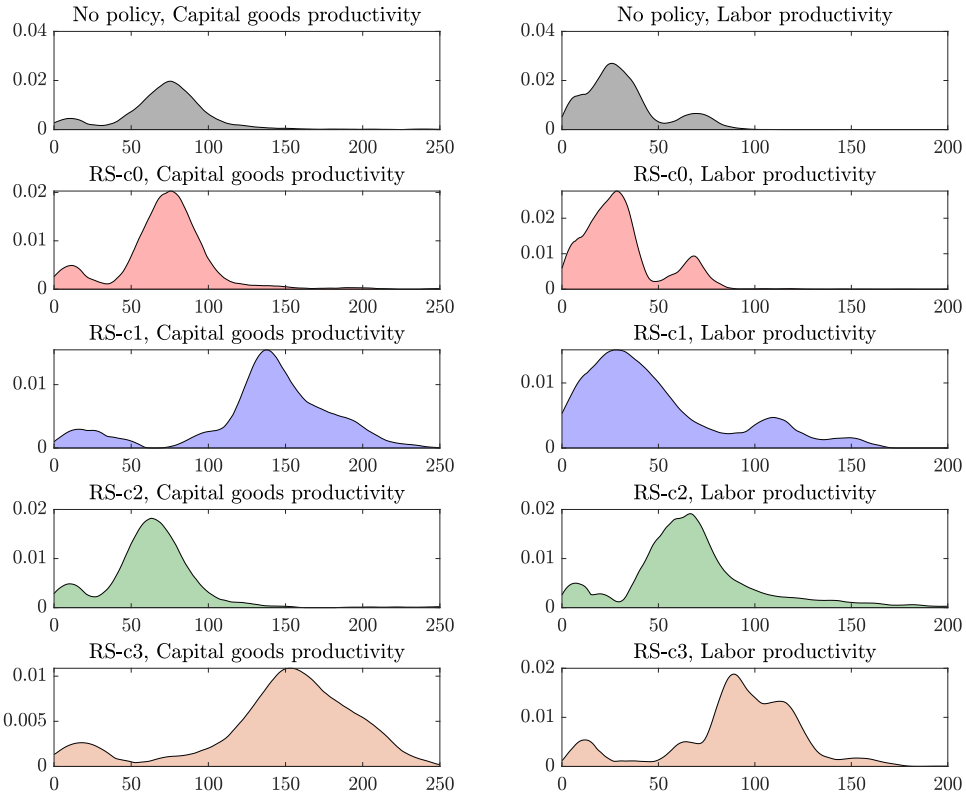


Figure 6: Kernel density function of capital-goods productivity and labour productivity at C-firms under alternative RS-c policy scenarios. Pooled observations from 100 MC simulations at $t = 2060$.

tendency to increased market power observed in the baseline.

In contrast, when R&D subsidies are combined with knowledge diffusion measures aimed at facilitating technology adoption (RS-c2, fourth row, green), the distribution of C-productivity shifts significantly to the right, reflecting a marked increase in average productivity among C-firms. More importantly, the configuration of the density changes from ML-FH in the baseline to FL-MH under RS-c2. In this scenario, C-firms cluster around a large number of leaders with high labour productivity and a small number of laggards with significantly lower productivity. By alleviating knowledge constraints among adopting firms, this policy mix enables laggards to access more advanced technologies, allowing them to *catch up* with leaders. The blended RS-c3 policy scenario (last row) shows higher averages of both K- and C- productivity, suggesting that more C-firms benefit from improved quality of machinery resulting from increased imitation.

Consider now Figure 7. A policy of pure R&D subsidies to innovators (RS-k0, red) results in

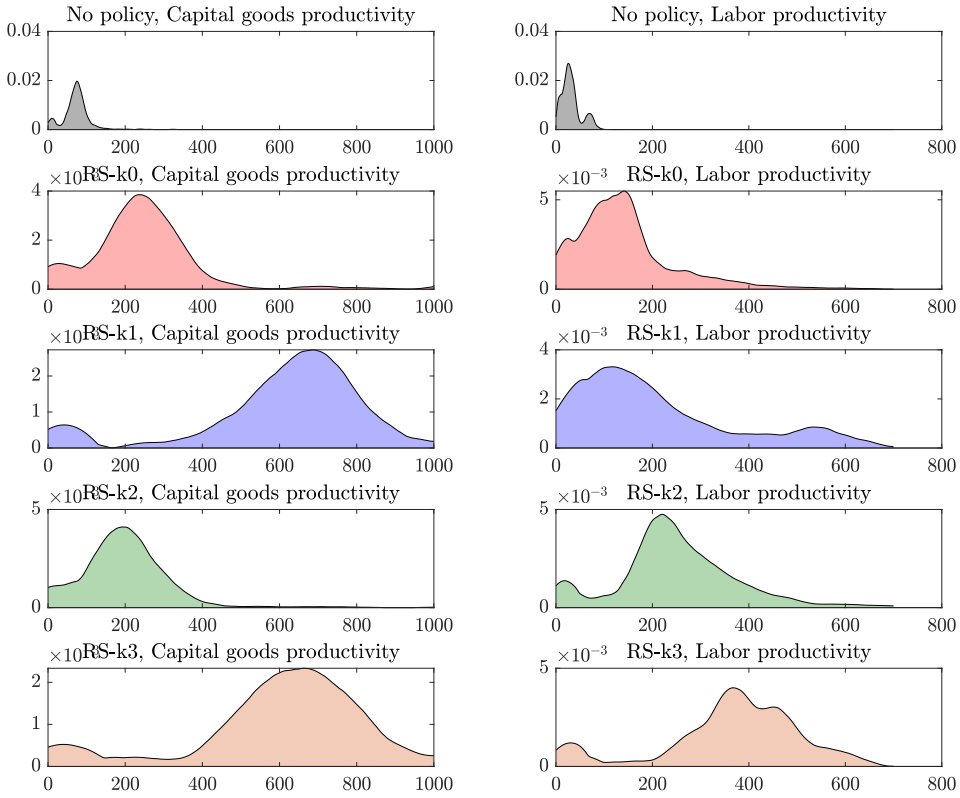


Figure 7: Kernel density function of capital-goods productivity and labour productivity under alternative RS-k policy scenarios. Pooled observations from 100 MC simulations at $t = 2060$.

a notable rightward shift of both density functions compared to the baseline. In the blended RS-k1 scenario (third row), the distribution of K-productivity shifts even further to the right, while the density of C-productivity also moves to the right, maintaining the ML-FH configuration. Recall that, although GDP growth improves under the RS-k1 scenario, there is an increase in market power relative to the no-policy scenario, as depicted in Figure 3. The reason for this phenomenon becomes clear from the third row of Figure 7: the extraordinary high quality of capital goods resulting from enhanced imitation (KD1) and subsidies to innovators (RS-k) creates a larger productivity gap compared to the RS-c1 case. Highly productive firms gain access to superior machinery, further widening the competitive advantage over laggards, which exacerbates market power and negatively impacts business dynamism.

The landscape changes dramatically when R&D subsidies are coupled with knowledge diffusion measures aimed at facilitating technology adoption (RS-k2). First, the distribution of K-productivity

remains largely unchanged compared to the baseline, while the distribution of C- productivity shifts significantly to the right, indicating a substantial increase in the average productivity of C-firms. Second, the configuration of the density of C-productivity transitions from ML-FH in the baseline to FL-MH under RS-k2. Finally, the blended RS-k3 policy scenario (last row) exhibits higher averages for both capital goods and labour productivity, suggesting a positive synergy between R&D and knowledge diffusion efforts. This combination fosters an environment where productivity gains are more broadly shared, leading to improved economic dynamics. We summarize these considerations in the following:

Result 3. ***RS and the density function of Productivity*** *A policy of pure research subsidies targeted at entrepreneurs (RS-c0) has essentially no effect on the position and shape of the density functions of K- and C-productivity. In contrast, if targeted at innovators, a policy of pure research subsidies (RS-k0) shifts both density functions significantly to the right, resulting in increased average K- and C-productivity and a wider productivity gap. A policy mix of RS and measures aimed at promoting imitation among K-firms (RS-c1 and RS-k1) also shifts the density functions of K- and C- productivity significantly to the right, yet it does not alter the baseline configurations of the density functions.*

Conversely, a policy mix of RS and measures aimed at promoting technology adoption by C-firms (RS-c2 and RS-k2) leads to (i) a rightward shift in the density of C-productivity; (ii) a significant change in its configuration to FL-MH (Few C-firms with Low productivity and Many C-firms with High productivity), contrasting with the ML-FH configuration of the baseline. In other words, this policy facilitates the catching-up process of laggards.

Discussion To make sense of these results, recall equation (7) that shows the positive relationship between the actual productivity of a machine tool adopted by a generic C-firm, say firm i, and the firm's *normalized* indicator of technical knowledge: $\hat{z}_i = \frac{z_i - z_{min}}{z_{max} - z_{min}}$. If research subsidies are distributed uniformly to C-firms (RS-c0), the normalized indicator of each firm does not change. Therefore, we expect a negligible effect on macroeconomic and cross sectional variables.

Things change when research subsidies to adopters are blended with knowledge intensive measures that mitigate the constraint on technological knowledge (RS-c2). When the constraint on technological knowledge goes down ($\gamma' < \gamma$), the actual productivity of machine tools goes up *for any firm and any level of knowledge*, with the exception of firms with very low technical knowledge. This is a tide that lifts (almost) all boats. Therefore, the composition of the population of adopters will change. The share of low quality adopters decreases and that of high quality adopters increases. Thanks to the mitigation of the constraint, in fact, a sizable part of previously low quality adopters gets access to the best technology, boosting actual productivity at the firm level. These new high quality adopters will experience a drop in marginal cost, they will reduce the price, increase the quantity produced and possibly their market share. Firms with very low technical knowledge stick to the old vintage, hence their marginal cost, price and the scale of production will not change.

Let's consider now policies that are targeted to innovators. Public transfers to innovators (RS-k0) will boost their R&D, thereby increasing the probability to innovate/imitate as shown by equations (13) and (14). Suppose now that on top of research subsidies, imitators benefit from regulatory measures that make imitation easier. When imitation capacity is strengthened (i.e., when ζ^{imi} increases), the probability of imitation increases *for any K-firm and the associated level of private R&D expenditure* A mix of research subsidies extended to imitators and a softening of patent protection boosts the impact on the probability of imitation.

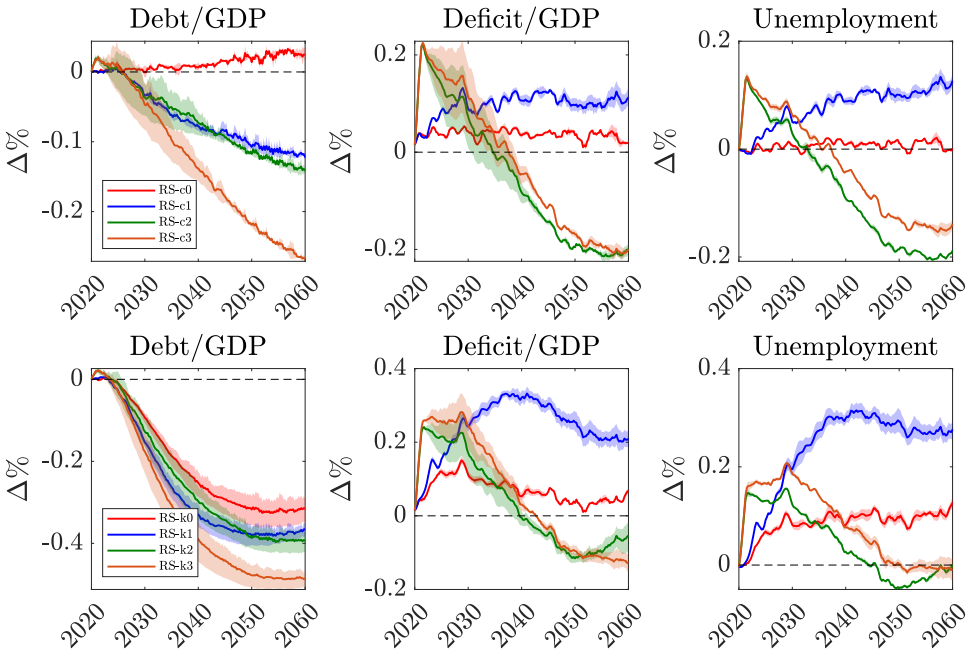


Figure 8: Effects of Research Subsidies for the C-sector (top) and K-sector (bottom) on public finances and unemployment rate under alternative RS policy scenarios.

The effects on public finance Figure 8 illustrates the effects of various industrial policies on public finances. Although the budget allocated to R&D subsidies is fixed across scenarios at 0.7% of 2020 U.S. nominal GDP, the relative impact on public finances depends on broader macroeconomic outcomes. Pure R&D subsidies lead to a gradual and sustained rise in the public deficit and, when targeting entrepreneurs (RS-c0), they also push the debt-to-GDP ratio up due to sluggish GDP growth. When combined with pro-imitation measures (RS-c1 and RS-k1, blue), these subsidies result in a higher deficit-to-GDP ratio due to weak business dynamism and rising unemployment. However, the long-run debt-to-GDP ratio declines as the growth rate surpasses the interest rate on government bonds. Only when R&D subsidies are combined with pro-adoption measures do we observe significant and lasting improvements in public finances. Under these scenarios, the deficit-

to-GDP ratio initially rises due to a temporary spike in unemployment, as labor productivity surges, especially among smaller firms. This technological unemployment, however, is short-lived; higher productivity eventually translates into wage growth, boosting aggregate demand and fostering a self-sustained growth process. It is crucial for the government to accommodate the short-term rise in unemployment benefits by tolerating a higher deficit, rather than imposing recessionary fiscal consolidation, which would risk stifling the recovery.

6.2 Adoption Policy

To explore the effects of Adoption Policy (AP) we follow the same procedure as in Section 6.1 for research subsidies. The model is simulated under the baseline scenario for 320 periods, or 80 years (starting in 1980), with the AP measures being introduced in 2020. We then compare the simulation outputs under each policy scenario with those of the baseline for the period 2020-2060.

Macroeconomic effects Figure 9 illustrates the mean percentage deviation of key economic indicators from the baseline scenario across 100 Monte Carlo simulations, capturing the effects of different AP interventions on real GDP, the productivity gap, market concentration, the weighted-average markup, and the labor share of GDP.[18] The policy scenarios include: Basic AP (BAP: red line), Knowledge-Intensive AP (KAP: blue), and the policy mix of Innovation and KAP (IAP: green) (for details on the institutional setting, we refer to Section 4.2).

From the top left panel of Figure 9, we observe that both BAP and KAP have a mild negative effect on GDP growth towards the end of the simulation period, as indicated by the red and blue lines falling below the x-axis. Under BAP, the productivity gap and concentration index are slightly lower than in the baseline scenario, while the effects on markup and wage share are less pronounced. Under KAP, the trend of increasing market power characterizing the baseline scenario is notably reversed. Specifically, the blue line shows a marked reduction in the productivity gap, accompanied by declining market concentration and markup, and an increase in the wage share.
In the case of IAP (represented in green), the trends in business indicators are similar to those observed under KAP, with the added benefit of higher GDP growth.

We summarize the macroeconomic effects of AP in the following:

Result 4. ***Adoption policy: Macroeconomic effects*** *Pure Adoption Policy has no significant effect on GDP (or a mildly negative one), both in the basic version (BAP) and complemented with a public research infrastructure (KAP). Only if mixed with a policy aimed at boosting innovation such as R&D subsidies to innovators (IAP), adoption policy enhances the growth rate of GDP. While BAP slightly mitigates the increase in the productivity gap and concentration observed in the no-policy scenario, it does not significantly alter the trend of rising markups and declining labor share. Only in the case of KAP and the policy mix IAP, there is a clear reversal of the tendency towards*

[18] Figure 16 in Appendix B.3 displays the same variables in absolute terms, rather than percentage changes, to provide additional insights into the evolution of key variables over time.

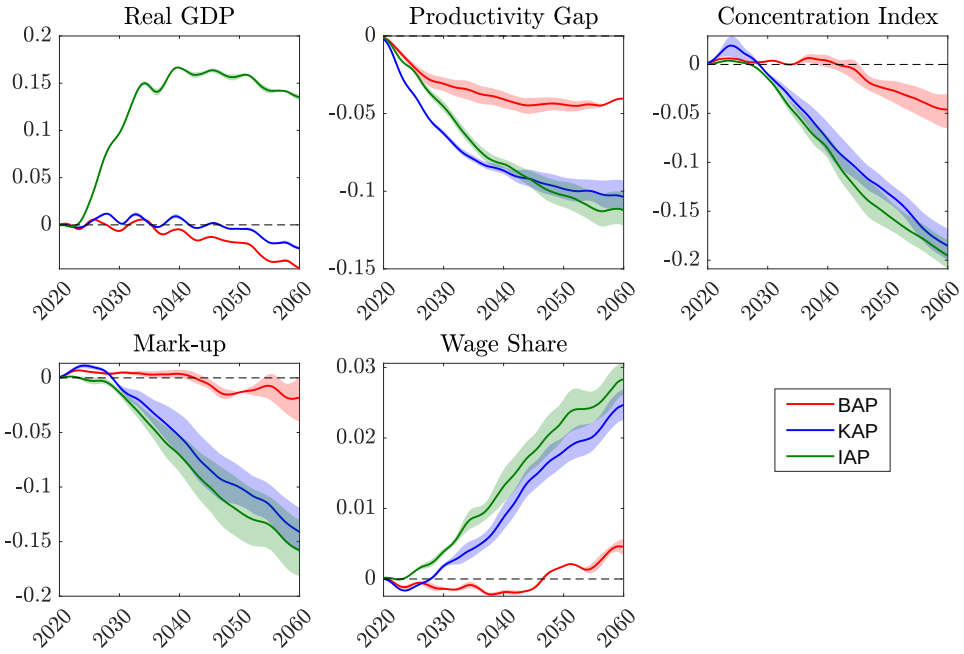


Figure 9: **Macroeconomic effects of Adoption Policy.** Policy scenarios: (i) Basic AP (red); (ii) Knowledge intensive AP (blue); (iii) policy mix of RS-k and Knowledge Diffusion AP (IAP, green). Solid lines represent the mean across 100 MC simulations; shaded areas represent 95% confidence intervals.

increasing market power: the productivity gap, concentration and the mark up decrease and the wage share increases. The growth rate of GDP, however, goes up only when the Government complements AP with policies targeted to innovators (IAP).

Cross-sectional effects Let's consider now the cross-sectional effects of adoption policy. From the left panel of Figure 10 we infer that BAP (red line) has no sizable effect on the dynamics of labour productivity: the red line is very close to the black one for every percentile.

When AP is knowledge-intensive (KAP, in blue), productivity growth is higher than in the baseline for each percentile, with the exception of the last one, and decreases with firm size. Under IAP (green), the growth of productivity is higher than under KAP for each percentile and, once again, negatively correlated with the level of productivity.

The market share growth exhibits a U-shaped pattern across all scenarios, with higher growth for small and large firms and lower growth for mid-sized firms. Yet, distinct differences emerge when compared to the no-policy scenario. Under BAP (red line, middle panel), market share growth is negative across all percentiles except for the largest firms. This indicates that BAP leads to a reduction in market share for small and medium-sized firms, further contributing to the polarization

of market power. However, up to the 60th percentile, BAP mitigates the decline in market share compared to the no-policy scenario (black line), whereas, for larger firms, it dampens market share growth. This outcome reflects the design of BAP, which primarily targets and benefits smaller firms. Under KAP (blue line) and IAP (green line), market share growth is positive for very small firms (20th percentile) and very large firms (100th percentile) but zero or negative for firms in the middle. These policies reduce the productivity gap between small and medium-sized firms, reinforcing their focus on supporting smaller firms while leaving mid-sized firms relatively disadvantaged.
Under the no-policy scenario, the growth rate of markups is negative across all percentiles, except for the highest. BAP positively affects the markup growth rate for firms up to the 60th percentile but fails to curb the growth rate of the largest firms' markups. In contrast, KAP and IAP have a pronounced impact: they significantly boost the markup growth rate for firms up to the 60th percentile while simultaneously suppressing the markup growth rate for firms in the 100th percentile.

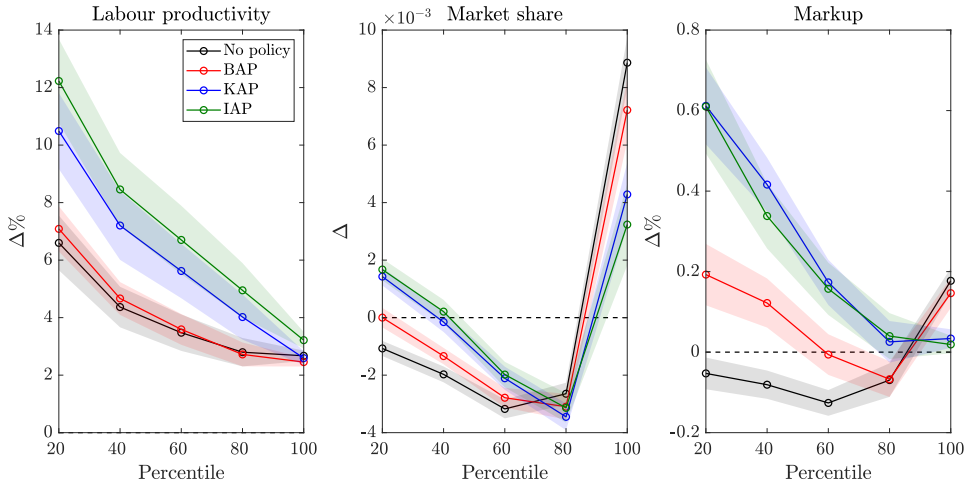


Figure 10: **Cross-sectional effects of Adoption Policy** Growth rate of labour productivity, market share and mark up across percentiles of the distribution of C-firms under AP experiments. Scenarios: (i) No-policy (black); (ii) Basic AP (red); (iii) Knowledge intensive AP (blue); (iv) policy mix of RS-k and KAP (IAP) (green). Solid lines represent the mean across 100 MC simulations; shaded areas represent 95% confidence intervals.

We summarize these considerations in the following:

Result 5. ***Adoption policies: Cross-sectional effects*** *Basic AP has little effect on productivity but exerts small yet significant effects on market share growth and markup growth rates. However, the increasing polarization of market shares observed in the no-policy scenario persists: firms with low market shares continue to lose ground, while those with high market shares further consolidate their position.*
In contrast, under KAP and IAP, productivity growth is higher than in the baseline, with the effect diminishing as firm size increases. Consequently, they contribute to narrowing the productivity gap

among firms. Additionally, KAP and IAP help mitigate the trend toward increasing polarization of both market shares and markups.

Density functions Figure 11 shows the estimated density function of the productivity of labour at C-firms (C-productivity) at the end of the simulation interval (period 2060) in the baseline (top row, left panel) and in all the AP scenarios.

We notice first that in all the scenarios densities are multi-modal. As mentioned above, in the absence of policy, the density function of C-productivity (top left panel) is essentially bimodal:[19] From visual inspection of the top right panel we conclude that BAP does not alter the position and the shape of the density function.

Under KAP (bottom left panel) and IAP (bottom right), the density function shift to the right (relative to the baseline) and the minor mode vanishes. These policies lead to an increase of the average productivity of C-firms.

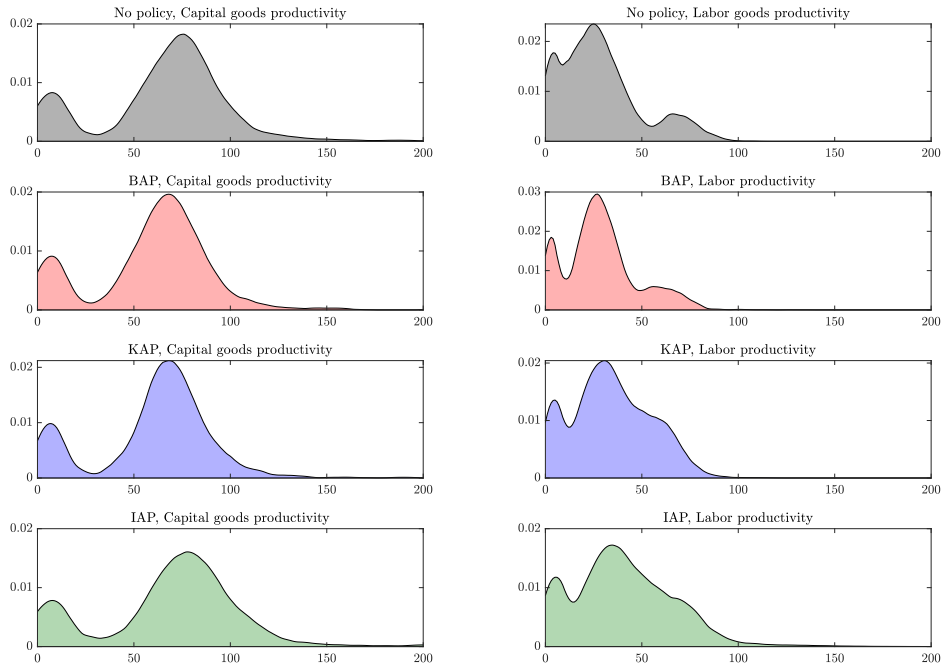


Figure 11: Kernel density function of capital-goods productivity and labour productivity under alternative AP experiments. Pooled observations from 100 MC simulations at $t = 2060$.

We summarize these considerations in the following:

[19] We abstracting from a third mode, which is very close to zero.

Result 6. ***AP and the density function of Productivity*** *BAP has essentially no effect on the position and shape of the density function. Under KAP and IAP the density functions shifts to the right and the minor mode vanishes.*

The results indicate that subsidizing capital replacement with new machinery, combined with knowledge transfer to adopters via public research infrastructure, reduces the productivity gap, as well as the differences in market shares and markups among entrepreneurs. This outcome is consistent with the findings from policy scenarios in which Research subsidies are blended with knowledge diffusion measures aimed at promoting technology adoption. Moreover, the temporary RS-k component in IAP boosts GDP growth, suggesting that a policy mix of research subsidies for innovators, adoption subsidies for entrepreneurs and knowledge transfers through public research infrastructure is highly effective.

7 Conclusions

In this paper, using a macroeconomic ABM, we have explored the role of industrial policy as a potential remedy to the decline in business dynamism associated to rising market concentration, declining labor share, and stagnant productivity growth that have characterize the macroeconomic landscape since the '80s. Our findings suggest that traditional measures, such as R&D subsidies and financial support for capital replacement, often fail to reverse these tendencies. Pure research subsidies targeted at entrepreneurs have negligible effects on GDP, while those targeted at innovators have a sizable effect on GDP but do not alter the trend of increasing market power observed in the no-policy scenario. A policy mix of subsidies with measures promoting imitation among K-firms leads to faster GDP growth but accelerates the increase in market power. Only when traditional measures such as R&D subsidies are combined with measures promoting technology adoption by entrepreneurs, faster GDP growth goes hand in hand with a reversal of the trend towards increasing market power: the productivity gap, concentration and the mark up decrease and the wage share rises.

Contrary to the emerging "Draghi consensus" in the EU, which advocates "scaling up" in key sectors to create European "champions", our results highlight the need for industrial policies that not only foster innovation but also enhance knowledge diffusion, bridging the knowledge gap among adopting firms and thereby ensuring that the benefits of innovation are widely shared. Industrial policies can unleash their full potential only if they reshape market structures and promote knowledge diffusion.

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Appendix A Parameter configuration

Table 4: Benchmark parameter setting

Symbol	Description	Value
W, F_c, F_k	Number of workers, C-firms, K-firms	1000, 100, 10
Z_c	Number of C-firms visited by each consumer	3
Z_{imi}	Number of K-firms visited by each imitator	3
Z_u	Number of firms visited by each unemployed worker	5
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
$\delta, \delta^{inv}, \delta^z$	Depreciation rate of capital, inventories, knowledge	0.03, 0.03, 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)

Appendix B Additional results

B.1 R&D subsidies with different allocation rules

So far we have conducted the R&D subsidy experiment assuming that all firms within the consumption or capital good sector receive the same amount of subsidies, namely $\alpha = 0$. It might be interesting to examine the effects of different types of allocation rules, either favouring the industry leaders ($\alpha > 0$) or followers ($\alpha < 0$).

Figure 12 presents the boxplots of the distribution of key variables from 50 Monte Carlo simulations, comparing the no-policy scenario with various allocation rules for the RS-c policy. We observe that when R&D subsidies are directed to the C-sector, regardless of whether they target the leaders (mission-oriented, RS-cm), laggards (diffusion-oriented, RS-cd), or adopt a neutral approach (RS-cn), the outcomes do not vary significantly. The reason is that, in the absence of specific measures prompting knowledge diffusion (KD), the competitive advantage of more productive firms companies is so high that R&D subsidies alone - even when predominantly allocated to less productive firms (RD-cd) - are insufficient to bridge the knowledge gap between industry leaders and followers amidst decades of declining business dynamism.

Nevertheless, when specifically targeting laggards (RS-cd), a reduction in the dispersion of GDP growth rates across simulations is observed. This is due to the positive stabilizing effects of subsidies to small firms, which mitigate their risk of default, thus curbing output volatility.

On the other hand, when examining alternative rules for allocating R&D subsidies directed to the K-sector (RS-k), we observe more distinct outcomes, although not markedly divergent, as illustrated in Figure 13. Specifically, we note that the highest median GDP growth rate is attained through neutral subsidy allocation, wherein subsidies are evenly distributed across all K-firms. In contrast, when targeting either the leaders or laggards, the median GDP is slightly lower. However, concerning other macroeconomic variables, results do not exhibit significant differences across rules.

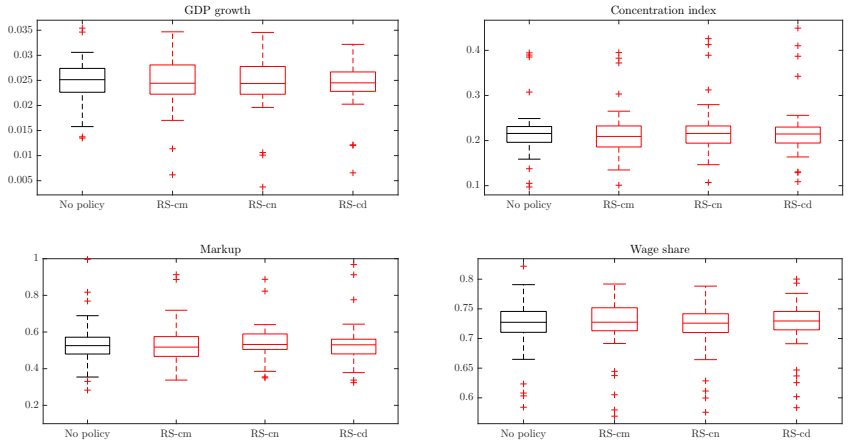


Figure 12: Boxplot of GDP growth, market concentration, markup and wage share from 50 MC simulations. Scenarios: No policy (black), Mission-oriented Industrial Policy for C-sector (RS-cm), Neutral Industrial Policy for C-sector (RS-cn), Diffusion-oriented Industrial Policy for C-sector (RS-cd)

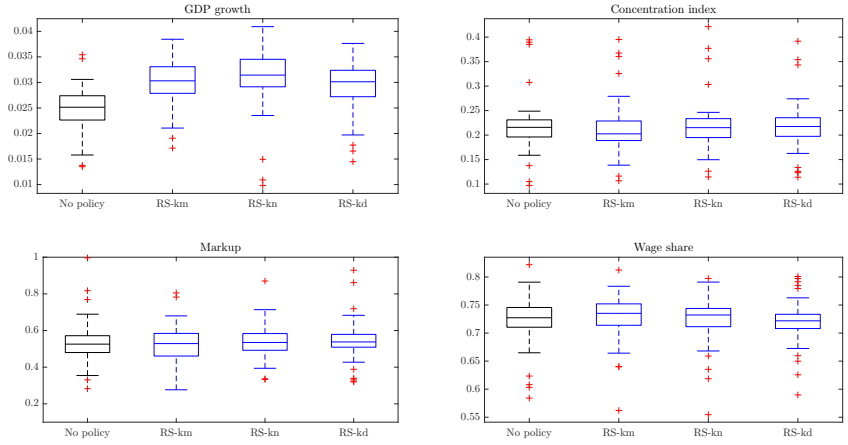


Figure 13: Boxplot of GDP growth, market concentration, markup and wage share from 50 MC simulations. Scenarios: No policy (black), Mission-oriented Industrial Policy for K-sector (RS-km), Neutral Industrial Policy for K-sector (RS-kn), Diffusion-oriented Industrial Policy for K-sector (RS-kd)

B.2 Experiment: R&D subsidies (RS)

Figure 14 and 15 show the effects of RS-c and RS-k policies, with and without complementary KD measures, on the level of real GDP, productivity gap, market concentration, mark-up and wage share over time.

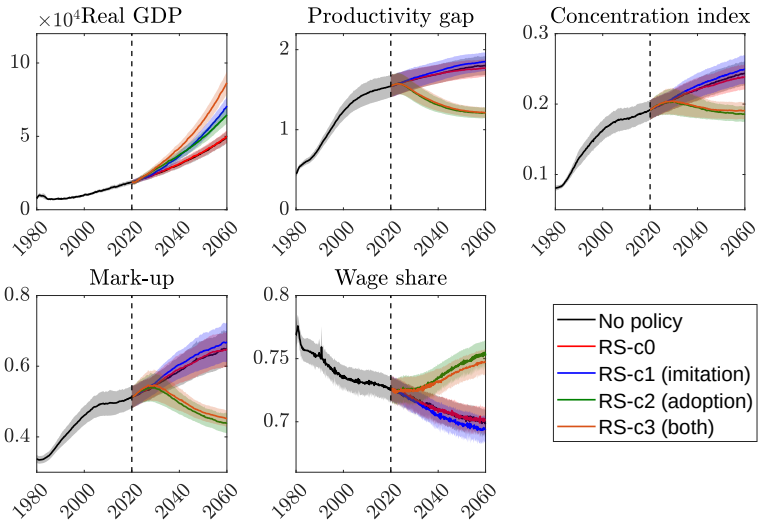


Figure 14: Effects of RS-c policy on real GDP, productivity gap, market concentration, markup and wage share. Mean values and 95% confidence interval from 100 MC simulations.

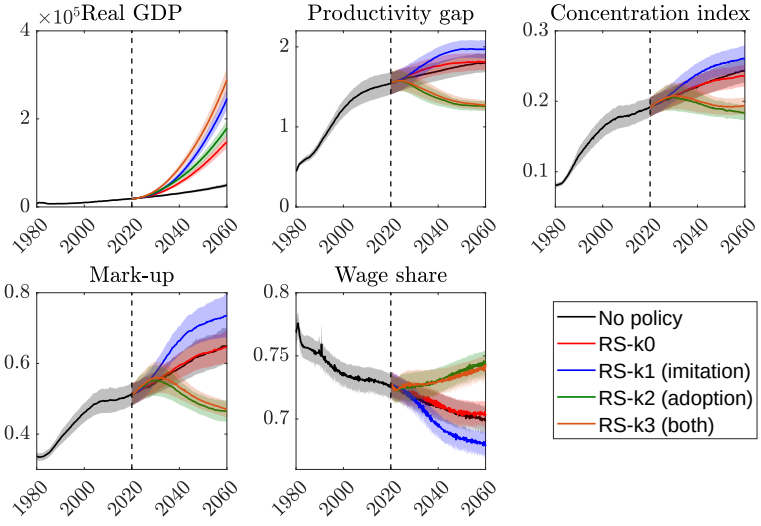


Figure 15: Effects of RS-k policy on real GDP, productivity gap, market concentration, markup and wage share. Mean values and 95% confidence interval from 100 MC simulations.

B.3 Experiment: Adoption policy (AP)

Figure 16 shows the effects of different types of adoption policy (BAP, KAP, IAP) on the level of real GDP, productivity gap, market concentration, mark-up and wage share over time.

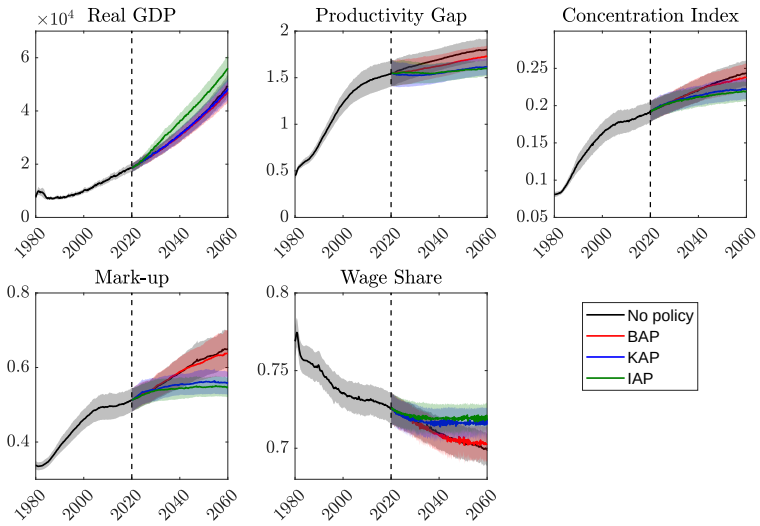


Figure 16: Effects of AP policy on real GDP, productivity gap, market concentration, markup and wage share. Mean values and 95% confidence interval from 100 MC simulations.