

Growth, Concentration and Inequality in a Unified Schumpeter Mark I + II model

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Abstract

I develop a simple Schumpeterian agent-based model where industries are born and evolve endogenously and use it to study the interrelation between technological change, economic growth, market concentration and inequality. This theoretical model combines features from the Schumpeter Mark I (centering around the entrepreneur) and Mark II model (emphasizing the innovative capacities of firms), and is capable of reproducing a large set of stylized facts concerning growth, market concentration, inequality and productivity. Among others, the model can reproduce the industry life-cycle, a Kuznets curve, a Piketty-style increase of inequality in “mature” economies, as well as recent stylized facts on “declining business dynamism”. I conduct an extensive policy analysis to identify the parameters that produce these stylized facts in the model. Notably, the empirically-grounded assumption that the difficulty to imitate a firm depends on its technological distance to the imitator can explain prominent stylized facts of economic development since the 1980s. However, growth in the number of industries triggered by the exploitation of new technological opportunities can prove to be a counteracting force to these tendencies in the short run. Thus, the model suggests a wave-like evolution of growth, inequality and market concentration centered around advances in basic research.

Keywords: Agent-based economics, Joseph Schumpeter, evolutionary economics, innovation

JEL-Codes: B25, C63, D33, L11, O11, O33, O41

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1 Introduction

Throughout capitalism’s history, mankind witnessed remarkable growth in productivity and product variety. This growth, however, has also been connected to persistent inequality. Ever since, economists investigated the causes, consequences and interrelation between these two key features of the prevalent economic system. While Kuznets famously proposed an inverted U-curve between economic development and inequality, i.e. that inequality would eventually decline once societies grew enough, the underlying empirical trend reversed in the 1980s (see Piketty 2014). Thus, the question of distribution, described by David Ricardo as the “principal problem in Political Economy” (Ricardo 1817, p.1), has reclaimed a prominent place in economics in the recent years.

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A number of different explanations have been put forward to explain the emergence, presence and rise of inequality. Although a clear distinction is not always possible, explanations may be attributed to at least one of three categories:

The first type of explanation argues that inequalities arise endogenously from economic processes that are inseparably connected to capitalism. This view is held by thinkers as important and diverse as Adam Smith, Joseph Schumpeter and Karl Marx, who approached this question from differing theoretical perspectives and normative points of view. While Marx (1890) emphasized a) the inequality *between* classes, which stems from and reproduces the “exploitation” of the working class and b) a tendency towards increasing concentration *within* the capitalist class, Smith saw inequalities arising from market processes as being “natural” and “useful” in contrast to “artificial” inequalities produced by policy (see Walraevens 2021). Schumpeter, an ardent defender of capitalism’s ability to encourage innovation and growth, characterized capitalism as “the civilization of inequality and of the family fortune” (p. 379). It is important to note that any serious economist – and especially neither of those named – would recognize that capitalism also embodies counteracting tendencies to at least some forms of inequality. If a certain business or production technology produces supernormal profits, others will try to enter this market or copy this technique and eventually drive down profits again. Nevertheless, De Loecker et al. (2020) show that both market power and profits have increased since the 1980s.

A second explanation attributes inequality to innovation and technological change. Not every reader of this paper will agree that this indeed represents an explanation worth separating from the first. Clearly, capitalism has been associated with technological progress over its entire history. However, both periods of rapid and sluggish technological change have been observed, and some of the underlying reasons are unlikely completely endogenous to economic processes. In particular, there has been a discussion about how computing technologies shape inequalities in the labor market, and whether technological change is directed by economic forces or technical properties (Acemoglu 1998; Acemoglu 2002; Autor et al. 1998; Autor et al. 2003; Mellacher and Scheuer 2021). Schumpeter stressed the ambivalent effects of innovation. In his “theory of economic development” (Schumpeter 1934), Schumpeter argued that entrepreneurial activity, i.e. innovation, is the main source of social mobility in capitalist societies, as successful entrepreneurs elevate their own position while creatively destroying the social position of some incumbents. Followingly, he argued that “the upper strata of society are like hotels which are indeed always full of people, but people who are forever changing. They consist of persons who are recruited from below to a much greater extent than many of us are willing to admit” (Schumpeter 1934, p. 156). Aghion et al. (2019) show that higher levels of innovation predict higher levels of top-income inequality and social mobility using data from the US. Ufuk and Akcigit (2021) discuss ten stylized facts on “declining business dynamism” since the 1980s, to which

they also attribute the rising market concentration and markups noted by De Loecker et al. (2020) and argue that a decrease in knowledge diffusion has the potential to explain these stylized facts.

The third type of explanations trace inequality back to social and/or political reasons. While Adam Smith argued that governmental policy creates inequality (Walraevens 2021), governmental activity is, at least in democracies, widely perceived to have reduced inequality. Recent empirical research has shown that minimum wage increases are able to increase wages at the lower end of the wage distribution with no or only a low effect on the level of unemployment (Cengiz et al. 2019; Derenoncourt and Montialoux 2021; Dustmann et al. 2021) and that unions significantly decrease inequality (Farber et al. 2021). A more general outlook on this topic is to assume that governmental activity creates or strengthens institutions which are fostering a reduction or increase in inequality (e.g. Acemoglu and Robinson 2002; Piketty and Saez 2014).

Without neglecting or downplaying the important role of social and political factors in determining the level of inequality, I focus on the first two types of explanations, i.e. innate tendencies of a capitalist market economy and technological change, by studying the following research question:

How are the birth and evolution of industries connected to growth, concentration and inequality?

In order to investigate this question within a suitable theoretical framework, I develop a rather simple Schumpeterian model that combines important features of the so-called Schumpeter Mark I model and the Mark II model. His Mark I model, developed in “*Theorie der wirtschaftlichen Entwicklung*” (Schumpeter 1911/34), centers around the entrepreneur, who disrupts the circular flow of the economy by using “new combinations”, i.e. by introducing new products, discovering new markets, improving the production processes etc. In his Mark II model, developed in “*Capitalism, Socialism and Democracy*” (2003[1942]), Schumpeter emphasizes the role of big corporations for technological progress. Pressured by competition, they must invest in Research & Development to continuously improve their products and cut their costs of production.

I formalize Schumpeter’s theories with an agent-based model that combines key features of Schumpeter Mark I and Mark II. In this unified model, entrepreneurs play the leading role in the birth of new industries. Entrepreneurs can on the one hand try to found industries by starting a new firm in a new industry, if they spot a possibility to do so, and on the other hand try to imitate existing firms. Firms invest in R&D to continuously improve their productivity and increase their profit rate, as well as push out their competitors. Firms engage in Cournot competition and the markup of each firm thus depends on the number of its competitors, as well as on its productivity relative to the productivity of the other firms in its industry.

I introduce a novel mechanism to *explain* the decrease in the diffusion of technological progress as identified by Ufuk and Akcigit (2021) to be a plausible factor causing the phenomenon of “declining business dynamism”, by introducing a technological distance penalty to imitation: If the productivity gap between a firm and the industry leader is bigger, it is harder for this firm to imitate. The same mechanism applies to entrepreneurs who want to enter a new industry by imitation. Thus, the role of the entrepreneur diminishes, and the role of the firm becomes more important once an industry becomes more mature. The basic mechanism, i.e. that the probability of knowledge spillovers between firms depends on their technological distance, is supported by empirical evidence (e.g. Bloom et al. 2013).

By being able to separate the creation of new industries from their evolution, this model is able to identify the importance of a) advances in basic research, and b) incremental innovation on the evolution of growth, concentration and inequality within a theoretical framework. My model thus allows for a more general level of analysis, accounting both for the possibility of an inverted U-curve relationship between economic development and inequality akin to the Kuznets-curve and for the empirically observed increase in inequality since the 1980s.

In addition to the vast stream of literature on the causes of inequality and, in particular, its interrelation with economic growth and technological change as outlined above, my paper contributes to four other, more specialized, strands of the literature:

First, to the formal modelling of endogenous technological change at the sectoral level inspired by Schumpeterian theories, which have made a big impact both in “mainstream” economics based on (general) equilibrium, starting with Romer (1990) and Aghion and Howitt (1992), as well as in evolutionary and agent-based economics, starting with Nelson and Winter (1982) and followed by many others.² In particular, the seminal contribution by Dosi et al. (2010) introduced endogenous technological change at the firm-level using a simple evolutionary process in the spirit of Nelson and Winter (1982) that has subsequently been applied to other macroeconomic agent-based models (ABMs) (e.g. Caiani et al. 2019; Terranova and Turco 2021). Other macroeconomic ABMs featuring endogenous technological change include the EURACE@Unibi model (Dawid et al. 2012) and the LAGOM model (Wolf et al. 2013). My contribution to this literature is a) to adapt the R&D mechanism by Dosi et al. (2010) to account (in a different way) for the empirical stylized fact that the technological distance between two firms influences the probability of knowledge spillovers and b) to allow for the

² See Dawid (2006) for an early overview of agent-based models on technological change

endogenous entry of new firms, depending on the availability of entrepreneurs who have enough funds to enter a new market and on their investment alternatives.

Second, I contribute to the literature on endogenous growth in the number of industries and products, most of which stand in the Schumpeterian tradition and some of which also feature a connection to inequality and/or labor market outcomes. This stream of literature has been pioneered by Saviotti and Pyka (2004a), who develop a model in which entrepreneurs endogenously create new sectors. Saviotti and Pyka (2004b; 2008) adapt this framework to study, among others, the impact of technological change on employment. In these models, new sectors are created once existing ones are “saturated” in the sense that they are devoid of monopoly profits. While I implicitly also include this mechanism as part of the short-sighted profit-maximizing behavior of entrepreneurs, my model also allows for (and witnesses) the (nearly) simultaneous creation of new sectors, depending on the availability of technological opportunities and entrepreneurial funds, as well as the level of concentration in the existing industries. Wersching (2010) develops a model in which Schumpeter Mark I and II represent mutually exclusive technological regimes, both of which are able to produce growth in the number of products. In contrast, my model integrates both Mark I and Mark II as different drivers of technological change into a unified model where the importance of both engines emerges endogenously from the model. Further related contributions contribute papers by Ciarli and Lorentz (2010), Savin and Egbetokun (2016), Vermeulen et al. (2018; 2020) and Gräbner and Hornykewycz (2021). The paper which is most related to my present work is by Dosi et al. (2021b), who develop a model of endogenous creation of new sectors based on the K+S framework (Dosi et al. 2010) and employ it to, *inter alia*, study the creation and destruction of labor. While their model is more complex in most respects such as with regard to the modelling of the labor and product markets, I contribute by modelling industry entry as an explicit action by entrepreneurs that is based on a probability to imitate which depends on the technological maturity of an industry. In particular, I show that my model is able to reproduce the dynamics observed since the 1980s with regard to inequality and “declining business dynamism”, while their model is currently set up to study the evolution of capitalism from WW2 to the late seventies (Dosi et al. 2021b, p. 4-5).

Third, I contribute to the literature on explaining inequality and labor market outcomes using broadly Schumpeterian models, which covers both contributions from general equilibrium theory (Aghion 2002; Aghion et al. 2019; Akcigit and Ates 2021; Jones and Kim 2018) and agent-based and disequilibrium models (Bordot and Lorentz 2021; Borsato 2020; Caiani et al. 2019; Fierro et al. 2021; Carvalho and Di Guilmi 2020; Dawid and Hepp 2021; Dosi et al. 2017; Dosi et al. 2018; Fanti 2021; Mellacher and Scheuer 2021; Terranova and Turco 2021). Among the general equilibrium models, my analysis is closest to the one by Akcigit and Ates (2021), who present ten stylized facts about “declining

business dynamism” and develop a simple model where a decrease in knowledge diffusion (i.e. imitation) can explain six out of these facts.³ They further argue that this factor has the potential to explain the other four stylized facts. I add to this literature by showing that a decrease in knowledge diffusion can indeed explain all of the ten stylized facts in a more complex model. Furthermore, I propose an explanation for a decreasing knowledge diffusion by considering the impact of technological distance and technological maturity of industries as the driving forces. Within the agent-based stream of this literature, my analysis is closest to Terranova and Turco (2021), who study how inequality and concentration are driven by (the absence of) knowledge spillovers building on fully-fledged macroeconomic ABM by Assenza et al. (2015) and extending it, *inter alia*, by the R&D mechanism from Dosi et al. (2010). My contribution to this literature is first to study the emergence and interrelation between innovation, imitation, concentration and inequality in a model where industries can endogenously be created. This is important, since my analysis shows that the creation of new sectors can have a counteracting effect on inequality and overall market concentration. Second, my analysis offers a potential *explanation* for the decrease in knowledge spillovers, i.e. imitation, using technological distance and maturity as outlined above and explicated in section 2.

Fourth, this paper contributes to the literature using agent-based models to study inequality and labor market dynamics. In addition to the papers mentioned in the preceding paragraphs, this literature also contains explanations for inequality that do not refer primarily to technological change, but e.g. to social networks (Gemkow and Neugart 2011; Dawid and Gemkow 2014), labor market regimes, wage setting policies and de-unionization (Caiani et al. 2020; Dawid et al. 2021; Dosi et al. 2017; Dosi et al. 2018; Dosi et al. 2021a), job mobility (Applegate and Janssen 2020) and more stylized approaches (e.g. Vallejos et al. 2018).

This paper does not aim or claim to provide a final analysis of the interrelation between growth, technological change and inequality. Instead, it aims to shed light on the interplay between economic processes innate to capitalism and technological change a) within an industry and b) creating new industries to uncover mechanisms that have the potential to explain some of the pressing issues of our time regarding growth, inequality and concentration. My analysis is complementary to other explanations of inequality and the method used in this paper, i.e. agent-based modelling, has indeed the potential to integrate multiple sources of inequality in a more general model at a later stage.

The rest of this paper is structured as follows: The second section describes the model. The third section explores the model’s ability to reproduce important stylized facts on growth, industry life-cycle,

³ Extending and using the model by Caiani et al. (2016), Reiter (2019) shows that a decrease in knowledge diffusion can explain at least 3 out of these stylized facts also in a fully-fledged macroeconomic ABM.

inequality and declining business dynamism and discusses the factors that produce these tendencies within the model. The fourth section concludes.

2 Model

The model mainly draws on three sources of inspiration:

First, following Joseph Schumpeter's theories, I consider two sources of innovation: On the one hand the entrepreneur, who is at the center of attention of Schumpeter's *Theorie der wirtschaftlichen Entwicklung* (Schumpeter 1911, in English: *Theory of Economic Development*, Schumpeter 1934) and on the other hand established firms, as discussed in his *Capitalism, Socialism and Democracy* (Schumpeter 1942). In my model, entrepreneurs play the leading role during the birth of new industries, by a) radically innovating, i.e. founding new industries by exploiting technological opportunities, and b) by imitating young firms in order to reap some of their surplus profits. I call this source the Mark I engine, following the popular characterization of the *Theorie der wirtschaftlichen Entwicklung* as Mark I by Christopher Freeman (1982, p. 212). Established firms, on the other hand, conduct research and development (R&D) in order to continuously improve their processes to improve their market position. I call this source the Mark II engine, following Freeman's (1982, p. 213) characterization of *Capitalism, Socialism and Democracy*. I further assume, following the empirical literature on this topic, that imitation becomes more difficult with an increasing technological distance. Hence, it becomes more difficult for entrepreneurs to enter existing markets after some time, and the importance of the Mark I engine diminishes once industries become mature and – vice versa – the importance of the Mark II engine grows over time, looking at a specific industry.

Second, following classical political economy, as well as an increasing fraction of evolutionary macroeconomics (e.g. Assenza et al. 2015; Borsato 2020; Mellacher 2020; Rengs and Scholz-Wäckerle 2019), the agents in my model are divided into classes, namely two: workers and entrepreneurs (who are also capitalists). This is a small deviation from Schumpeter (1911), who argued that the capitalist and the entrepreneur are different actors. Also, for simplicity, and because it is not the focus of my analysis, I follow classical political economy in assuming that each goods market and each labor market are cleared during each time step of the simulation. It is important to note, however, that this does *not* imply general equilibrium or even partial equilibrium beyond the ultra-short run, as I assume that the agents are boundedly rational and imperfectly informed about the capabilities and strategies chosen by the other agents.

My third source of inspiration is evolutionary economics. Modelling technological change *within sectors* as a two-step stochastic process involving evolutionary selection was pioneered by Nelson and Winter (1982), and later refined and introduced as the standard agent-based macroeconomic approach by Dosi et al. (2010). I use an adapted version of this approach to model the Schumpeter Mark II engine, i.e. technological change *within* each sector.

This model is an agent-based model, i.e. it centers around explicitly modeled heterogeneous interacting agents whose behavior is described in this section. Figure 1 gives an overview of the model, which is described in detail in the following subsections. Each worker agent works at a specific industry (subsection 2.3). Each industry is located at one technological opportunity (subsection 2.4). The number of technological opportunities may grow over time due to advances in basic research, but are, following Schumpeter (see Freeman 1982), exogenous to the economic processes depicted in the model. Each firm is located at a single industry, where it conducts R&D (covering both invention and imitation) to improve its productivity and engages in (boundedly rational) Cournot competition (subsection 2.2). Entrepreneurs own firms and live off their profits. They consume a fraction of their funds and save the rest to finance new firms. Entrepreneurs can try to a) found new firms by radically innovating, i.e. trying to exploit an unused technological opportunity by founding a new firm in a new industry, or b) imitate an existing firm (subsection 2.5). Households, i.e. workers and entrepreneurs, consume from industries by splitting their consumption budget evenly among industries with a positive output (2.1).

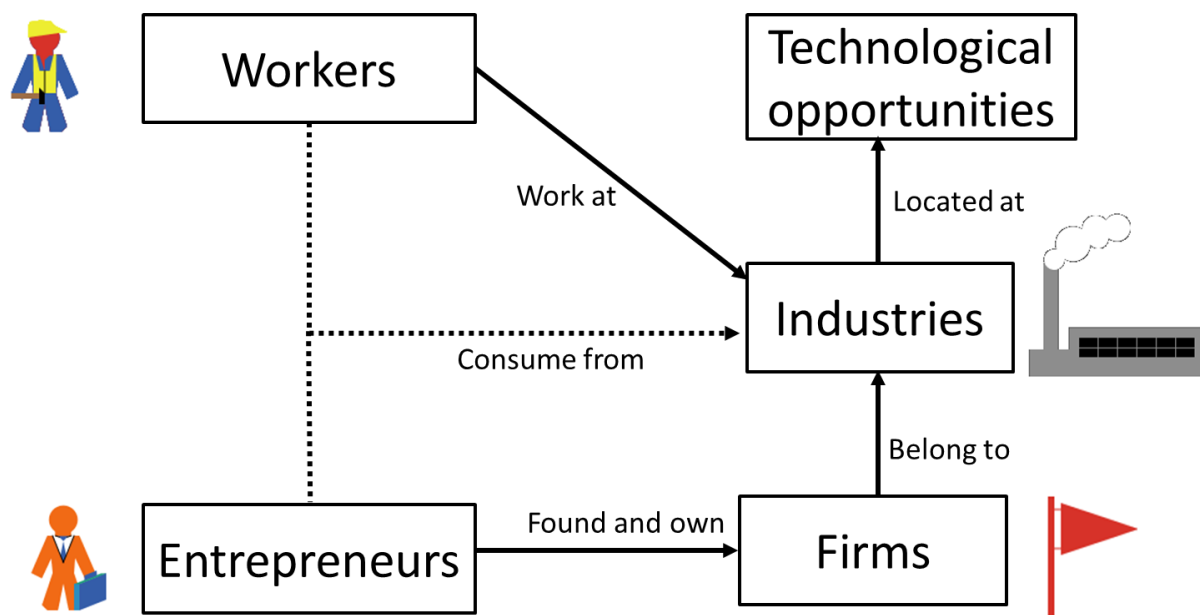


Figure 1: Overview of the model

My model is discrete-time. In each time step of the simulation:

1. Technological opportunities are updated
2. Entrepreneurs decide whether they want to try to imitate or radically innovate
3. Workers decide at which industry they want to work
4. Firms decide about their labor market demand
5. Labor market interactions are processed
6. Firms perform research and development
7. Firms produce their output
8. Firms pay wages and rents
9. Households consume
10. Firms calculate their profits
11. Statistics are updated

2.1 Households and consumption

The model is populated by n households, which are split into two classes of agents who behave fundamentally differently: workers and entrepreneurs. In the beginning of the simulation, n_0^w agents are initialized as workers and n_0^e agents are initialized as entrepreneurs. The number of entrepreneurs and workers in the model is to a certain degree endogenous: Whenever the last firm of an entrepreneur goes bankrupt, she will become a worker.

Workers are employed in an industry k , where they receive a wage rate $w_{k,t}$ which is specific to the industry and time period t . They consume all of their income and may move between industries, if the differences in the industry-specific wage rates are too high. The exact mechanism is described in subsection 2.3.2.

Entrepreneurs own firms and obtain their profits. More specifically, firms pay out the difference between revenues in the last period and wage payments of the current period to their owner.⁴ Entrepreneurs save a fraction τ of their available funds and consume the rest. The funds of entrepreneur y ($f_{y,t}$) are thus updated according to the following equation, where $q_{i,t-1}^{actual}$ denotes the production of the firm i , $n_{y,t}^i$ the number of firms owned by y , $p_{k,t-t}$ the price of the industry and $q_{i,t-t}^{actual}$ the firm's production in the previous period, $w_{k,t}$ the industry's wage rate and $l_{i,t}$ the firm's labor force in the current period:

⁴ If the economy was in a stationary equilibrium, this would be equal to the profits of the current period.

$$f_{y,t} = f_{y,t-1}\tau + \sum_i^{n_{y,t}^i} (q_{i,t-t}^{actual} p_{k,t-t} - w_{k,t} l_{i,t})$$

Total nominal demand d_t is thus given as follows, where $w_{x,t}$ denotes the wage of worker x , $f_{y,t}$ is the funds of entrepreneur y , n_t^w is the number of workers and n_t^e the number of entrepreneurs in the current period.

$$d_t = \sum_x^{n_t^w} w_{x,t} + \sum_y^{n_t^e} (1 - \tau) f_{y,t}$$

Total nominal demand is then allocated evenly to each active industry according to the following formula, where $d_{k,t}$ denotes the industry-specific nominal demand and n_t^k the number of industries that produce a quantity which is larger than 0:

$$d_{k,t} = \frac{d_t}{n_t^k}$$

While this mechanism is highly simplified, it is easily understandable, while still able to capture a salient feature of Schumpeterian thought, namely creative destruction: the foundation of a new industry tears away demand from the old industries, thus causing a recession in those industries and subsequently a reallocation of demand towards the new industry.

2.2 Firms

Firms hire workers to produce a specified good and to engage in research and development (R&D) activities. They are confined to a single industry each and engage in Cournot competition with the other firms which are active in this industry. Each firm belongs to a single entrepreneur, and each entrepreneur may have at maximum one firm in each industry.

2.2.1 Production planning

Following the simplified specification of the demand for the various consumption goods industries, firms engage in Cournot competition, i.e. try to set their quantity such that they maximize their profits. In contrast to an equilibrium-based model, however, I do not presuppose any equilibrium. Firms know about the total nominal demand for an industry in the previous period, as well as total output in the previous period. They do not, however, possess knowledge about the output decision of their competitors or any of the production technologies that will be used in the current period. As a

heuristic, firms assume during their production planning that the output of their competitors, as well as their own labor productivity remains constant. Followingly, firms first compute the Cournot quantity $q_{i,t}^{Cournot}$ using nominal demand observed in this sector in the previous period $d_{k,t-1}$ and past supply of their competitors $q_{i,t-1}^{comp} = \sum_{i' \neq i} q_{i',t-1}$, where i' is active in the same industry as i .

$$q_{i,t}^{Cournot} = \sqrt{\frac{d_{k,t-1} * q_{i,t-1}^{comp}}{\frac{w_{k,t}}{a_{i,t-1}}}} - q_{i,t-1}^{comp}$$

2.2.2 Nominal labor demand

The nominal Cournot labor demand $l_{i,t}^C$ is then computed by adding a constant fraction ν of labor dedicated to research and development to the amount of labor necessary to produce the Cournot quantity and multiplying it with the industry's wage rate:

$$l_{i,t}^C = w_{k,t} \frac{q_{i,t}^{Cournot}}{a_{i,t-1}} (1 + \nu)$$

However, firms do not directly choose $l_{i,t}^C$, as it is calculated based on the other firms' output in the previous period. As these firms will likely adjust their production into the same direction, choosing $l_{i,t}^C$ would cause a firm to "overshoot", meaning that they would increase or decrease their production too much. Instead, they follow a parameter-free heuristic that allows firms to slowly adapt their production towards the optimal Cournot quantity (which itself slowly adapts towards actual production) without such an "overshooting" and industries to approach an equilibrium in absence of technological change, which is also based on their actual nominal labor demand in the previous period $l_{i,t-1}^d$ and the number of firms in this industry $n_{k,t}^i$ ⁵:

$$l_{i,t}^{dC} = l_{i,t}^C + \frac{l_{i,t-1}^d - l_{i,t}^C}{1 + \frac{1}{n_{k,t}^i - 1}}$$

Besides technological change within the industry and its associated uncertainties, as well as uncertainty with regard to the actions taken by the competitors (which firms deal with using the heuristics above), Cournot competition fails to capture another crucial aspect of competition within my model: namely, the endogenous entry of new firms into an industry. By producing low quantities,

⁵ Please note that this formula is only calculated if the firm is not a monopolist, as labor demand is $l_{i,t}^{dmin}$ in this case (see the next paragraph).

a monopolist incentivizes imitation. Thus, it is reasonable for firms who command a large market share (such as monopolists) to produce a larger quantity than the Cournot quantity. This idea is also captured by a simple heuristic: If the expected rate of profit from producing the Cournot quantity lies above a rate of profit of r^{target} , the nominal labor demand is set to produce an expected rate of profit of r^{target} .

$$l_{i,t}^{dmin} = \frac{q_{i,t-t}^{actual} p_{k,t-t}}{1 + r^{target}}$$

Actual labor demand $l_{i,t}^d$ is thus $l_{i,t}^{dmin}$ or $l_{i,t}^{dC}$, whichever is higher, but at maximum the funds which the firm currently has at its disposal (i.e. its revenue in the previous period):

$$l_{i,t}^d = \min(q_{i,t-t}^{actual} p_{k,t-t}, \max(l_{i,t}^{dmin}, l_{i,t}^{dC}))$$

Exceptions are given for firms which operate in an industry where total production in the previous period was 0. In the first time step of the simulation, nominal labor demand equals the entire funds a firm has at its disposal. If a firm produces for the first time in a new industry after the first time step (i.e. after a radical innovation), it aims to achieve r^{target} by producing $l_{i,t}^{dfounder}$, but is constrained by its funds $f_{i,t}$, where d_{t-1} is the total nominal demand observed in the previous period and n_{t-1}^k is the number of industries that had an output larger than 0 in the previous period:

$$l_{i,t}^{dfounder} = \frac{\frac{d_{t-1}}{n_{t-1}^k + 1}}{(1 + r^{target})}$$

$$l_{i,t}^d = \min(f_{i,t}, l_{i,t}^{dfounder})$$

2.2.3 Research and development

R&D activities in my model capture both innovation and imitation, and follow the standard logic as developed in the Keynes + Schumpeter model by Dosi et al. (2010) closely, with the exception of the imitation process, which I changed to account for the stylized fact that it seems to be harder to enter a technologically advanced industry than to enter an infant industry. It is important to note that Dosi et al. (2010) also implemented a mechanism to incorporate “technological distance” between the imitating firm and the imitated firms. In their model, however, the technological distance does not affect the *overall* chance for a successful imitation, but the *target* of the imitation process, i.e. it is more probable to imitate a technologically close competitor. I, in contrast, assume that firms would

always want to imitate their best competitor and that the chance to do so decreases with the technological distance between the two firms, as measured by the difference in labor productivities.

Firms hire an additional fixed share ν of their production staff to engage in R&D. A fraction ξ of the R&D staff is assigned to innovation, the rest to imitation. Firms which are at the technological frontier dedicate all of their efforts to innovation, which is consistent with the empirics (Liao 2020).

The innovation process is given by a three-step process. First, a draw from a Bernoulli distribution decides whether a firm successfully invents a new production technology. The parameter of the distribution, $\theta_{i,t}^{IN}$, is given as follows, where $l_{i,t}^{IN}$ denotes the number of workers who are assigned to innovation by firm i in period t and ψ^{IN} is a parameter:

$$\theta_{i,t}^{IN} = 1 - e^{-\psi^{IN} l_{i,t}^{IN}}$$

From this equation, copied exactly from Dosi et al. (2010), it is clear that the probability of a successful innovation increases with the number of workers assigned to innovation, but that this increase is subject to diminishing returns.

The second step of the innovation process occurs if the Bernoulli draw was successful. In this case, a productivity change $\Delta a_{i,t}^*$ is drawn from a normal distribution with the mean μ and the standard deviation σ . The productivity of a newly invented production technology $a_{i,t}^*$ is thus described by the following equation, where $a_{i,t-1}$ denotes the production technology used in the previous period:

$$a_{i,t}^* = a_{i,t-1}(1 + \Delta a_{i,t}^*)$$

In the third step, firms compare the invention with the existing technology. Only if $a_{i,t}^* > a_{i,t-1}$, the invention will actually be adopted, i.e. cause an innovation, and become $a_{i,t}$.

After processing innovation activities, firms try to imitate their best competitor. More specifically, they try to copy the most productive technology used in their industry during the last period. Similar to the innovation process, the probability of a successful imitation depends on a draw from a Bernoulli distribution. The Bernoulli parameter $\theta_{i,t}^{IM}$, is given as follows, where $l_{i,t}^{IM}$ denotes the number of workers who are assigned to imitation, ψ^{IM} is an imitation capability parameter, $a_{i,t}$ the labor productivity of the firm after computing innovations, $\bar{a}_{k,t-1}$ is the highest labor productivity in industry k (i.e. the industry in which firm i is active) in the previous period and ϑ is an imitation distance penalty parameter. The reasoning behind this specification, which makes it harder for a laggard to catch up with a frontier firm if the technology gap between the two firms widens is described above.

$$\theta_{i,t}^{IM} = 1 - e^{\frac{-\psi^{IM}}{(1+\vartheta)(\bar{a}_{k,t-1}-a_{i,t})}} l_{i,t}^{IM}$$

If the imitation is successful and more productive than the currently used technology (even after accounting for a possible invention), the firm adopts this technology.

2.2.3 Production

After accounting for R&D, those workers who are not assigned to R&D, i.e. $l_{i,t}^{prod}$, produce consumption goods using the technology described by the labor productivity $a_{i,t}$.

$$q_{i,t}^{actual} = l_{i,t}^{prod} a_{i,t}$$

2.3 Labor market

The labor market is, just as the goods market, highly simplified as it is not the focus of my current analysis. The nominal labor demand of firms has already been described in subsection 2.2.2.

2.3.1 Wage rate

Workers have a fixed reservation wage w^r , which is set to allow for a full-employment equilibrium in the absence of profits. It is given by the following equation, where $f_{i,0}$ denotes the initial funds of each firm in period 0, n_0^w the initial number of workers and n_0^i the initial number of firms:

$$w^r = \frac{n_0^i f_{i,0}}{n_0^w}$$

Each worker in industry k supplies a fraction of labor taking into account the total number of workers in this industry $n_{k,t}^w$, as well as nominal labor demand in this industry $l_{k,t}^d$, which is the sum of nominal labor demand of all firms active in this industry.

$$l_{x,t}^s = \min\left(1, \frac{l_{k,t}^d}{n_{k,t}^w}\right)$$

The nominal wage rate *per worker* in industry k ($w_{k,t}$) is then calculated as follows:

$$w_{k,t} = \frac{l_{k,t}^d}{\sum_x n_{k,t}^w l_{x,t}^s}$$

It is important to note that the nominal wage rate per *unit of labor* is fixed to w^r , following the specification of labor supply.

2.3.2 Inter-industry labor reallocation

During each time step of the simulation, workers may “move” between industries based on the relative nominal labor demand in each industry in the previous period. More specifically, a target number of workers in each industry $n_{k,t}^{w*}$ is determined by relative the nominal labor demand in each industry of the past period and the total number of workers n_t^w .

$$n_{k,t}^{w*} = \frac{l_{k,t-1}^d}{\sum l_{k,t-1}^d} n_t^w$$

If the number of workers in a given industry is below this target, workers are reallocated from industries where the number of workers is above its respective target.

2.4 Technological opportunities

Technological opportunities represent a potential product space, which is exogenously determined by advances in basic research and which can endogenously be exploited by entrepreneurs to found new industries. This assumption is in line with Schumpeterian theory (see Freeman 1982). Technological opportunities are given by a $m \times n$ matrix, where each element of the matrix represents one potential industry. Scientific advances may change m and n . More specifically, m may increase with the probability φ^m and n with the probability φ^n at the beginning of each time step of the simulation if the maximum size of the product space has not been reached yet. A technological opportunity may become an actual industry, if an entrepreneur successfully carries out a radical innovation, which is described in the next subsection.

2.5 Entrepreneurs

Entrepreneurs are at the heart of the “Schumpeter Mark I” engine of this model. During each time step, they try to found a new firm by either a) imitating in an industry where they do not yet own any firm (if such an industry exists) or b) radically innovating by founding a new industry in an unexploited technological opportunity (if such a technological opportunity exists). The probability of a successful radical innovation is given by ρ .

In deciding what to do, entrepreneurs compare the expected profit of their investment, which is equal to their current funds $f_{y,t}$. The expected profit of pursuing a radical innovation $E(\Pi_{y,t}^{radical})$ is given by the probability to successfully conduct a radical innovation ρ , the expected wage payments, i.e. the expected nominal labor demand of the firm $l_{i,t}^d$ and the expected nominal demand of the industry $d_{k,t}^{expected}$:

$$E(\Pi_{y,t}^{radical}) = \rho(d_{k,t}^{expected} - l_{i,t}^d)$$

The expected nominal demand of the industry is given by the following equation, where d_{t-1} denotes total nominal demand of the past period and n_{t-1}^k the number of industries with an output which is larger than 0:

$$d_{k,t}^{expected} = \frac{d_{t-1}}{n_{t-1}^k + 1}$$

The expected nominal labor demand of the new firm founded by a radical innovation is given by the following equation, where π denotes the target rate of profit:

$$l_{i,t}^d = \min\left(f_{y,t}, \frac{d_{k,t}^{expected}}{1 + \pi}\right)$$

The expected value of pursuing an imitation is more demanding, as we have to calculate the imitation probability, as well as the Cournot quantity. The imitation probability follows the imitation mechanism at the firm-level, but replaces $l_{i,t}^{IM}$ with 1 (i.e. the entrepreneur):

$$\theta_{y,t}^{IM} = 1 - e^{\frac{-\psi^{IM}}{(1+\vartheta)(\bar{a}_{k,t-1} - a_0)}}$$

The expected value of trying to imitate $E(\Pi_{y,t}^{imitation})$ is thus given by the following equation:

$$E(\Pi_{y,t}^{imitation}) = \theta_{y,t}^{IM}(d_{k,t}^{expected} - l_{i,t}^d)$$

Where the expected nominal demand is thought to remain constant, i.e. $d_{k,t}^{expected} = d_{k,t-1}$ and labor demand is

$$l_{i,t}^d = \min(f_{y,t}, l_{i,t}^C)$$

Where $l_{i,t}^C$ is calculated in the same way as it is for existing firms.

Entrepreneurs will only become active once they are able to attract at least one worker with their savings, i.e. they need to accumulate at least some savings to be able to found a new sector.

3 Results

In this section, I a) explore the model's ability to reproduce empirical stylized facts, and b) identify the parameter settings associated with these stylized facts to explore how they are in my model.

In discussing the results, I refer to two crucial concepts: the "Mark I engine" and the "Mark II engine". The Mark I engine describes the process in which entrepreneurs found new firms by radically innovating or by imitating their competitors. This engine is particularly important in the presence of unexploited technological opportunities. The Mark II engine, on the other hand, captures R&D at the firm-level. R&D ensures that industries evolve and labor productivity increases within each industry.

In order to better understand the effects of these "engines", I test the impact of changes in a) the imitation distance penalty (determining the ability of laggards to imitate the industry leader), and b) the arrival of new technological opportunities (enabling entrepreneurs to radically innovate by founding a new industry) on the model's ability to replicate each stylized fact.

The model is implemented in NetLogo (Wilensky 1999). Each parameter combination is run 50 times with fixed random seeds. The figures show the results of quantile regressions produced with the ggplot2 (Wickham 2016) package for R (R Core Team 2020). The baseline parameters are set as following:

Parameter	Value
invention standard deviation	0.025
initial funds available per firm	10
initial number of entrepreneurs	100
initial number of workers	10000
likelihood of a radical innovation	0.01
propensity to invest in R&D	0.05
imitation likelihood parameter	0.3
invention likelihood parameter	0.3
target profit rate	0.2
imitation distance parameter	0/0.1/0.5
share of R&D staff assigned to invention	0.5
initial technological opportunities occupied	0.5
initial labor productivity	1
propensity of entrepreneurs to save	0.2

initial technological opportunities (x)	5
initial technological opportunities (y)	5
target technological opportunities after arrival of new opportunities (x)	10
target technological opportunities after arrival of new opportunities (y)	10
arrival of target technological opportunities	1000 / never

In section 3.5, I carry out policy scenarios to further investigate how the other parameters influence the results.

3.1 Industry-level SF:

This model is primarily a model of the birth and evolution of new industries. Hence, its ability to replicate industry-level stylized facts is of utmost importance. Although not all industries evolve equally, a characteristic pattern of industry evolution can be found in manufacturing industries: The number of firms over time follows an inverted U-curve pattern (**SFI1**): it first increases rapidly, before declining again (Gort and Klepper 1982). The price decreases (**SFI2**), but with a falling rate (**SFI3**). The output increases (**SFI4**), but with a falling rate (**SFI5**), see Klepper and Graddy (1990) and Dinlersoz and MacDonald (2009).

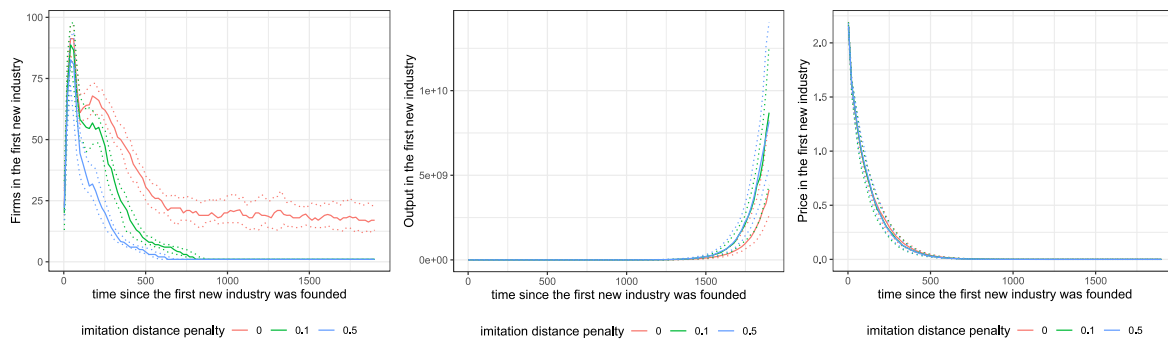


Figure 2: The number of firms (upper left), output (upper right) and price (bottom left) in the first new industry, i.e. the first industry founded by entrepreneurs. The timescale shows the number of time steps that passed since the first new industry was founded, i.e. refers to different time steps in each simulation run, depending on the first successful radical innovation.

Fig. 2 shows that the inverted U-curve relationship for the number of firms, the increase in output and decrease in price can be observed for any parameter setup (**SFI1**, **SFI2**, **SFI4**). This is not always the case, however, for the falling rate of decrease in price (**SFI3**) and increase in output (**SFI5**). While this seems to be true for the median run in any setup involving a positive imitation distance parameter (indicated by the quantile regressions), linear models suggest that these stylized facts can only be replicated if new technological opportunities arrive, see fig. 3.

Growth, Concentration and Inequality in a Unified Schumpeter Mark I + II Model

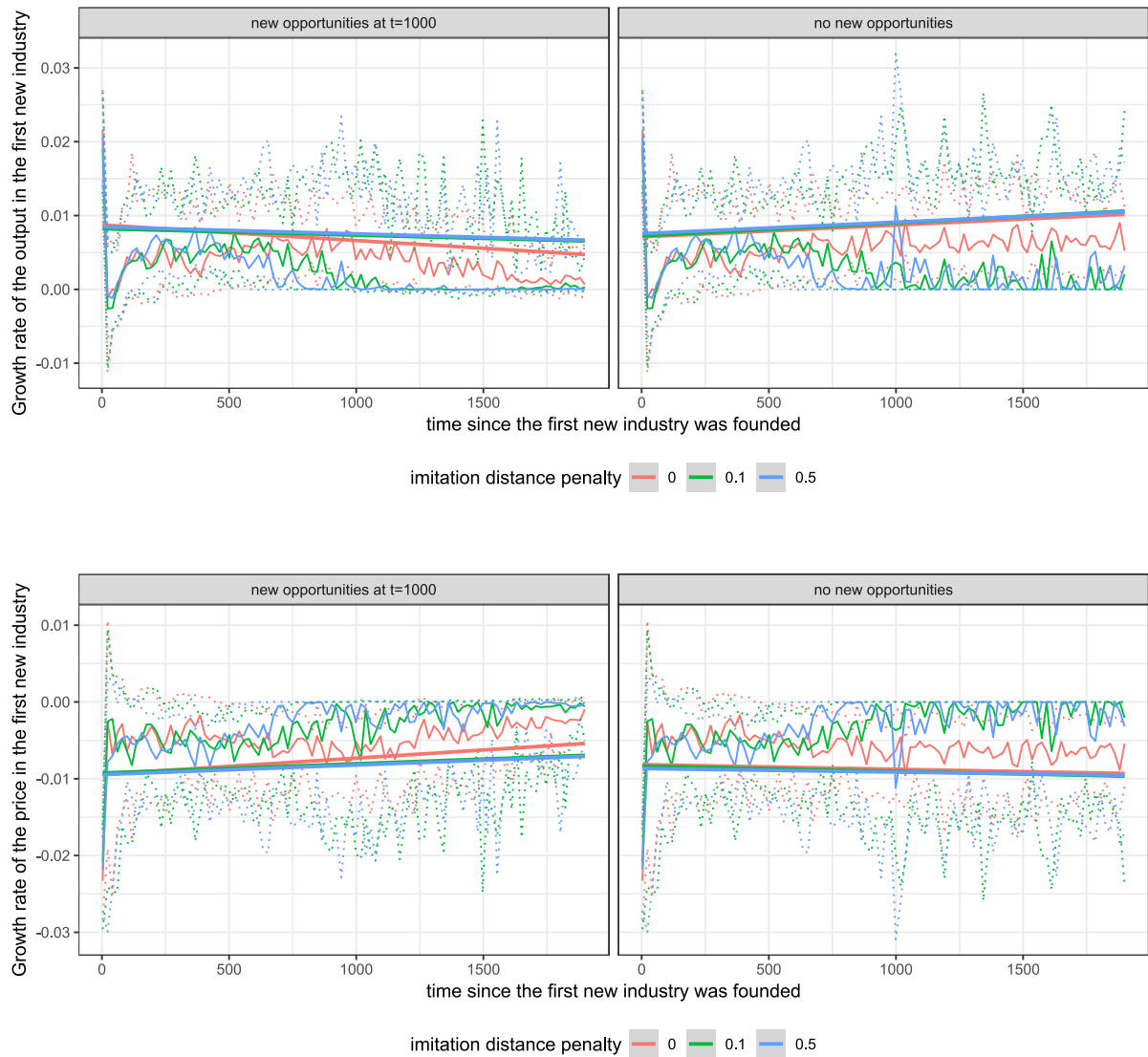


Figure 3: Growth rate in output (top) and price (bottom) for different setups, as indicated by quantile regressions and linear models.

3.2 Inequality over time

Driven by the empirical observations at his time, Simon Kuznets (1955) famously proposed the so-called Kuznets curve that exhibits an inverted U-curve relationship between economic development and inequality. This means that inequality rises first, only to peak and decrease again, once economies become mature (**SFK**). Piketty (2014), on the other hand, showed that this decrease was followed by an increase in inequality since the 1980s (**SFP**). As it can be seen from figure 4, computing the Gini coefficient of income, my model is able to capture both tendencies. The Mark I engine creates a wave-like inequality: entrepreneurs found new industries, thus benefitting from surplus profits (i.e.

monopoly rents) in the beginning. Soon after, however, competitors manage to enter these new industries via the means of imitation, thus pushing profits down. Over time, all of the technological opportunities are exploited, thus making imitation even more attractive, which further pushes inequality down. Afterwards, the Mark II engine becomes dominant. If there is no penalty on imitation activities based on the technological distance, inequality remains fairly stable. If there is such a penalty, however, firms which are at the technological frontier are more successful in pushing their competitors out of business and the Mark I engine fails to compensate for the decreasing competition, as it becomes harder for new firms to enter mature industries. Thus, more and more “winner takes it all” industries emerge, which increase global inequality over time, resembling the relationship between development and inequality observed by Piketty (2014).

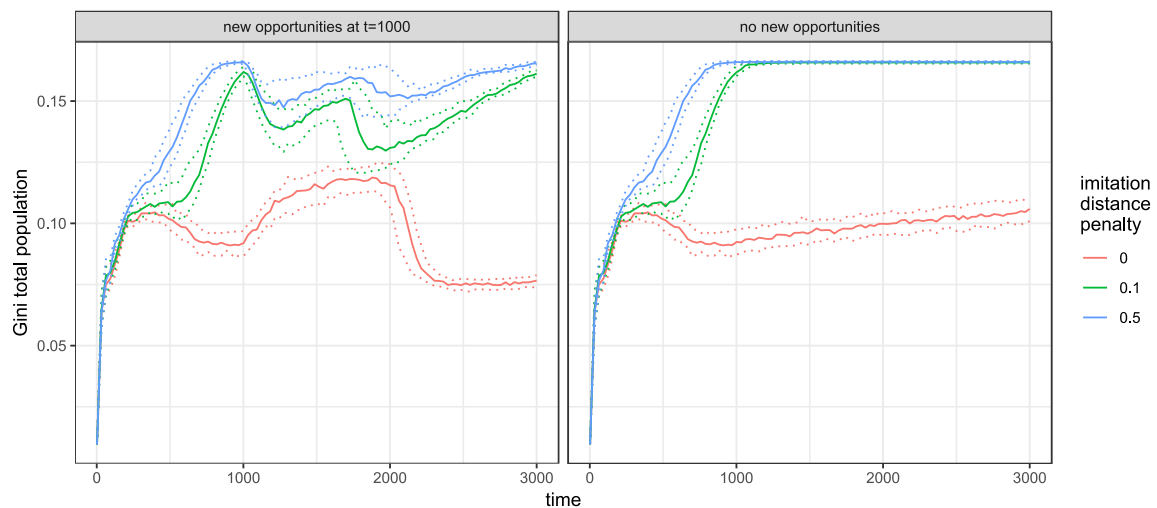


Figure 4: Inequality over time as measured by the Gini of the funds possessed by the total population

3.3 Stylized Facts on declining business dynamism

Furthermore, a “Piketty” scenario is in my model, as in the real world, accompanied with the 10 stylized facts on “declining business dynamism” proposed by Akcigit and Ates (2021), which I number from **SFD1-SFD10**. As it can be seen, the extent of these tendencies crucially depends on both a) the imitation distance penalty parameter and b) the arrival of new technological opportunities.

As already noted by Autor et al. (2017, 2020), market concentration has risen from the 1980s to the 2010s, and this increase in concentration has been associated with a fall in the labor share. Figure 5 shows the average Hirschmann-Herfindahl-Index (HHI) over all industries, where 1 indicates complete market concentration (i.e. each industry is dominated by a single firm) and 0 atomistic competition. As

argued above, the Schumpeter Mark I engine creates a wave-like form of market concentration, whereas the Mark II engine produces a secular increase in market concentration, if there exists some imitation distance penalty parameter. This long-term increase can be counterbalanced, however, by the arrival of new technological opportunities, which would restart the Mark I engine by activating it in these new industries. We can see that the extent of this increase (**SFD1**) thus does in my model not only hinge on a decrease in knowledge diffusion, as suggested by Akcigit and Ates (2021), but also on the scarcity of fresh technological opportunities for altogether new industries.

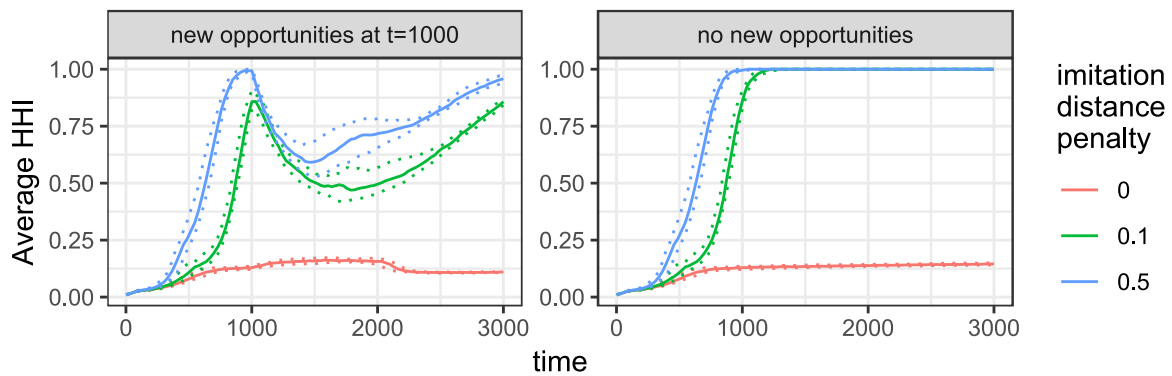


Figure 5: Average Hirschmann-Herfindahl Index across all industries

Figure 6 shows the evolution of average markups. Since markups increase with market concentration in a Cournot model, they move into the same direction as the average HHI, i.e. increase in the “Piketty-scenarios” (**SFD2**). Since labor is the only production input, the rate of profit equals the markup and thus behaves accordingly (**SFD3**).

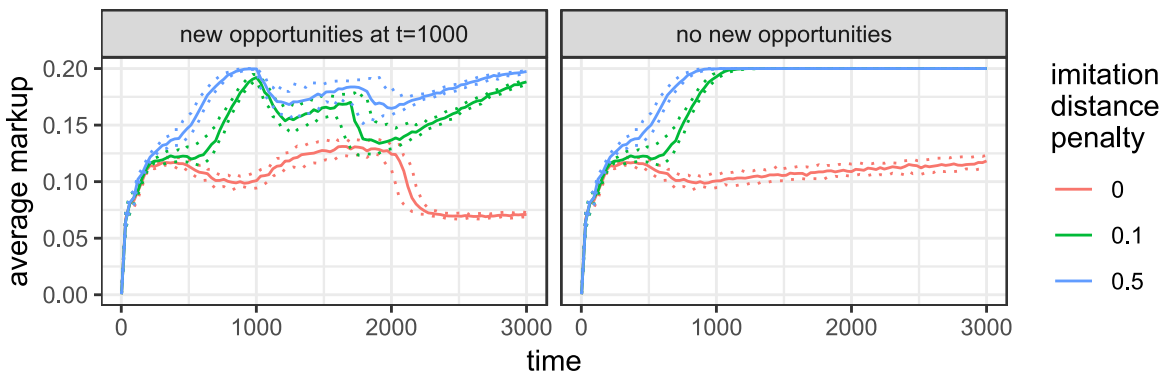


Figure 6: Average markups across all industries

The wage share decreases (**SFD4**) in a “Piketty-scenario”, since it behaves inversely to market concentration and markups (**SFD5**), as can be seen in fig. 7.

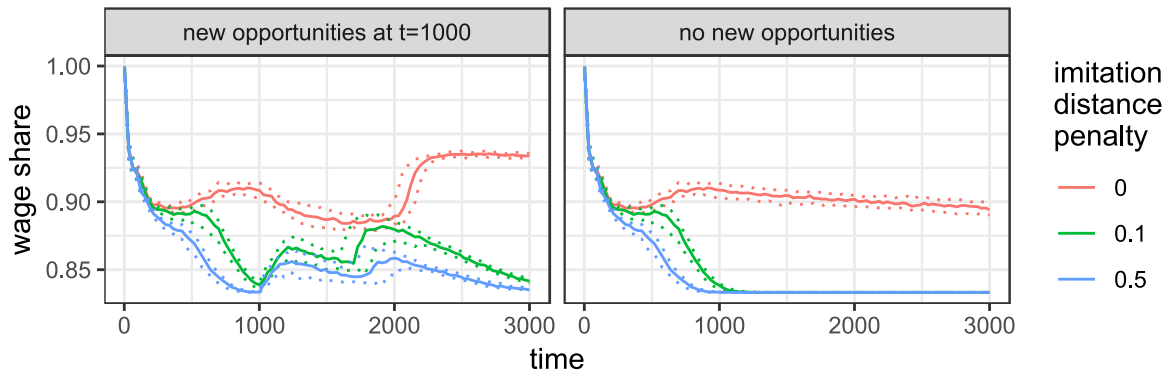


Figure 7: Evolution of the wage share over time

Figure 8 shows the labor productivity gap between the frontier firms (i.e. the most productive firm in each industry) and the rest of the industry. While the Mark II engine increases this lag, the Mark I engine can reduce it (since new entrants copy the production technology used by the frontier firm in the previous period). In addition to a wave-like increase that mirrors the increase in market concentration, inequality and average markup, the average productivity lag becomes larger (**SFD6**) in the scenarios characterized by a low total number of technological opportunities and presence of an imitation distance penalty.

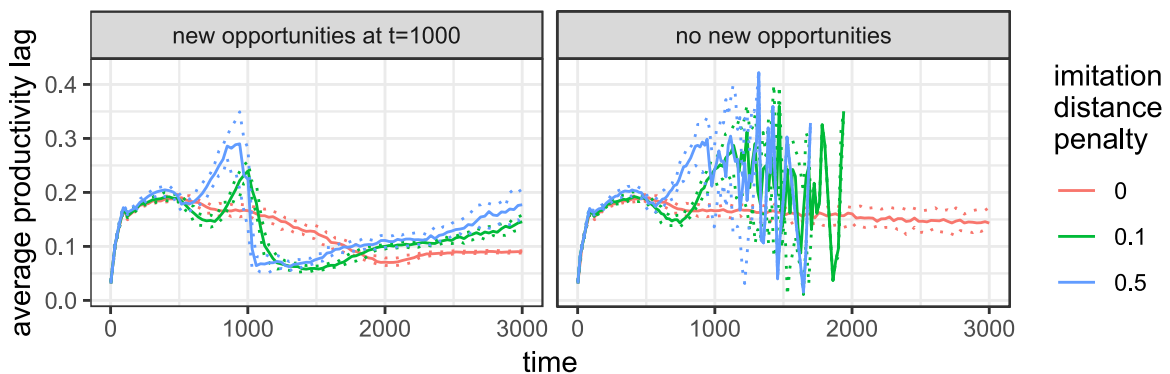


Figure 8: Average productivity lag between the frontier firm and the laggards. Note that the lag is not calculated, if there are no laggards.

Figure 9 shows the evolution of the number of firm entries. It can be seen that it is deeply interconnected with the current utilization of technological opportunities. If it is possible and profitable for entrepreneurs to pursue a radical innovation, firm entries are on average lower, as radical innovation is more difficult. Once all opportunities are exploited, however, firm entries increase again, as the relatively high market concentration allowed entrepreneurs to accumulate enough funds to enter new industries. It then decreases again (**SFD7**), especially in the presence an imitation distance penalty.

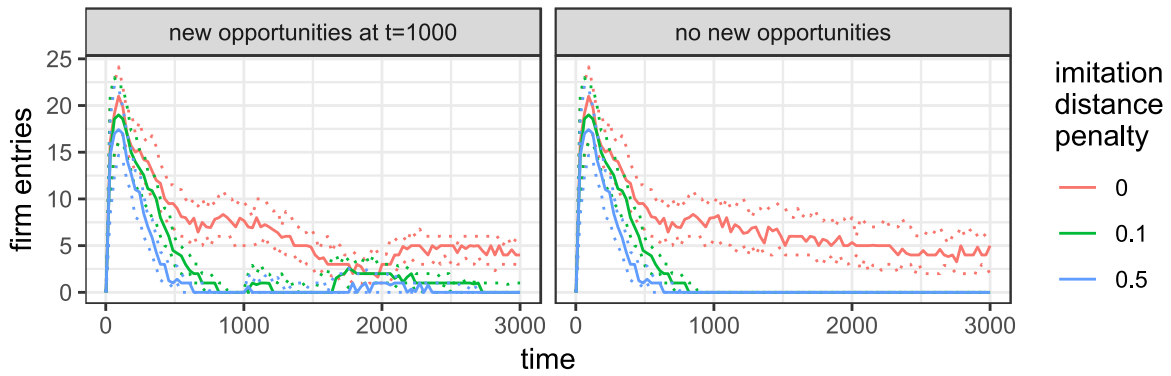


Figure 9: Evolution of firm industries in all industries over time

Figure 10 shows the employment share of young firms, where a young firm is defined as one created at most 50 periods ago. In line with **SFD8**, this share decreases over time if all technological opportunities are used and there is an imitation distance penalty. Naturally it increases, on the other hand, if new industries are founded, as firms in my model are confined to a single industry.

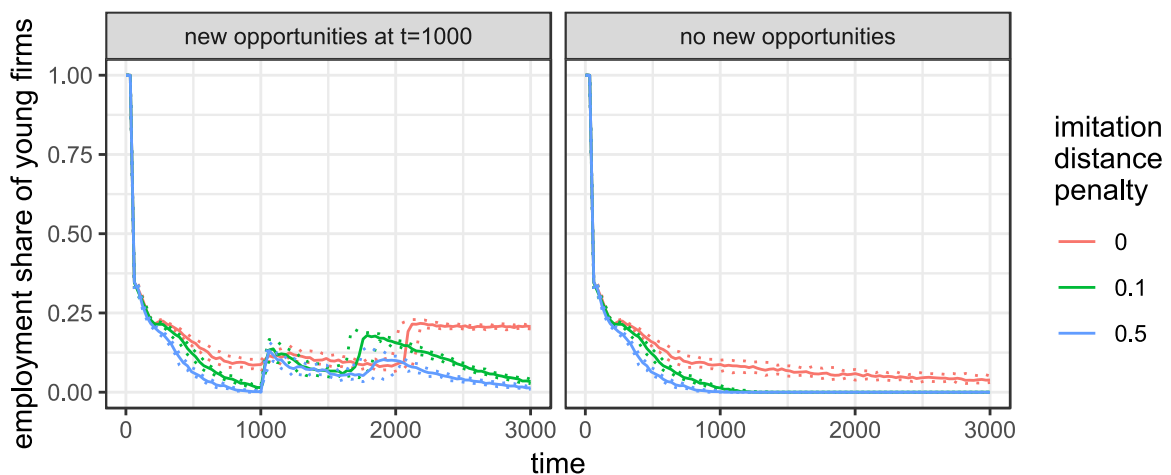


Figure 10: Share of workers employed by young firms (at most 50 periods old)

Figure 11 depicts the evolution of total employment over time. In the absence of births and deaths, the empirically observed decrease job reallocation (i.e. the sum of job creation and destruction) translates into a decrease in total employment. In line with **SFD9**, job reallocation decreases in the presence of an imitation distance penalty. In addition to that, employment is subject to creative

destruction upon the birth of new industries, as labor demand in new industries cannot fully make up the lost labor demand in old industries, as new industries are more concentrated.

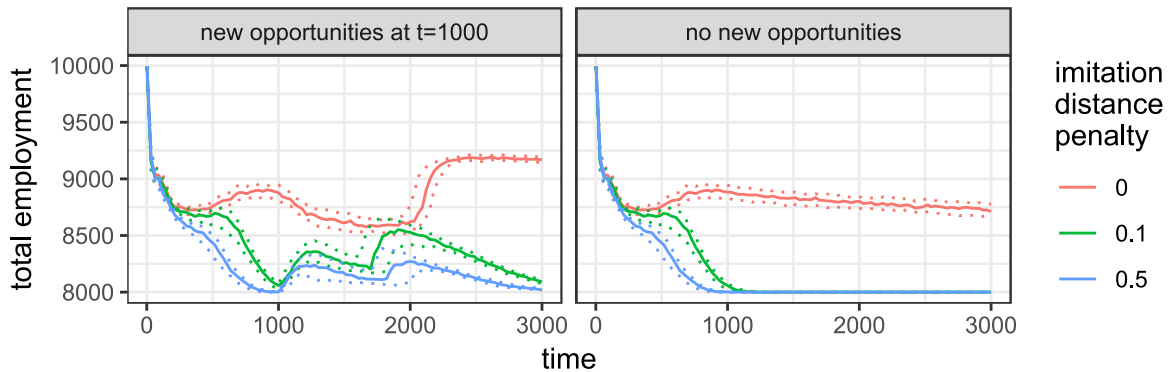


Figure 11: Total employment in number of worker agents over time.

Figure 12 shows the dispersion of firm growth rates measured by the standard deviation of productivity growth. In line with **SFD10**, it decreases in the long run with an increase in market concentration.

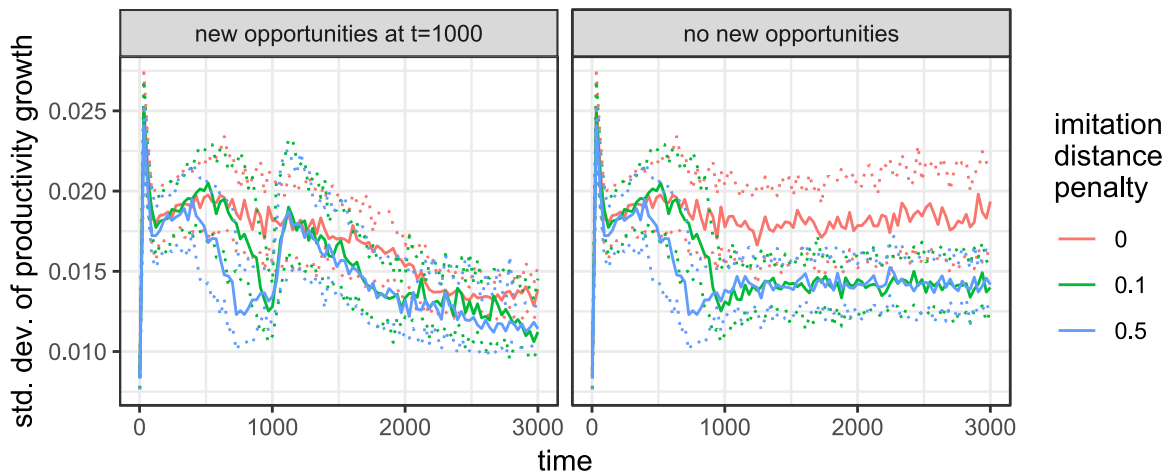


Figure 12: Standard deviation of productivity growth over time.

3.4 Top income inequality

Two analyses based on a fusion of Schumpeterian theories and general equilibrium reached contradictory results: While Aghion et al. (2019) find a positive correlation between innovation and top income inequality, Kim and Jones (2018) see creative destruction, i.e. innovation, as a counteracting force. What does the unified Schumpeter Mark I+2 model say about top income inequality and concentration within the class of entrepreneurs? Figure 13 shows a Gini index of the

combined market share of entrepreneurs, which captures inter-industry market concentration and, by extension, also top income inequality through the channels discussed in the previous subsection. This Gini index is calculated by adding up all market shares of firms owned by each entrepreneur. This analysis is complementary to the Hirschmann-Herfindahl-Index shown in fig. 5, as it is possible to have perfect market concentration in each industry, while at the same time maintaining perfect equality between the entrepreneurs by having each industry dominated by a single firm owned by a different entrepreneur.

Interestingly, it can be seen in fig. 13 that the absence of an imitation distance penalty can actually increase the long-run power concentration within the class of entrepreneurs, since it is then easier for entrepreneurs who have success in a number of industries to translate their success to other industries by entering them. Creative destruction in the form of the creation of new industries is indeed able to reduce this form of inequality, although this process takes much longer, if the inequality between entrepreneurs is very high (in these simulations: if no imitation distance penalty exists), as new entrants first have to gather the funds necessary to enter a new industry. Also, the simulations suggest a non-linear relationship between the imitation distance penalty and top income inequality / combined market concentration, as the intermediate value produces the lowest inequality.

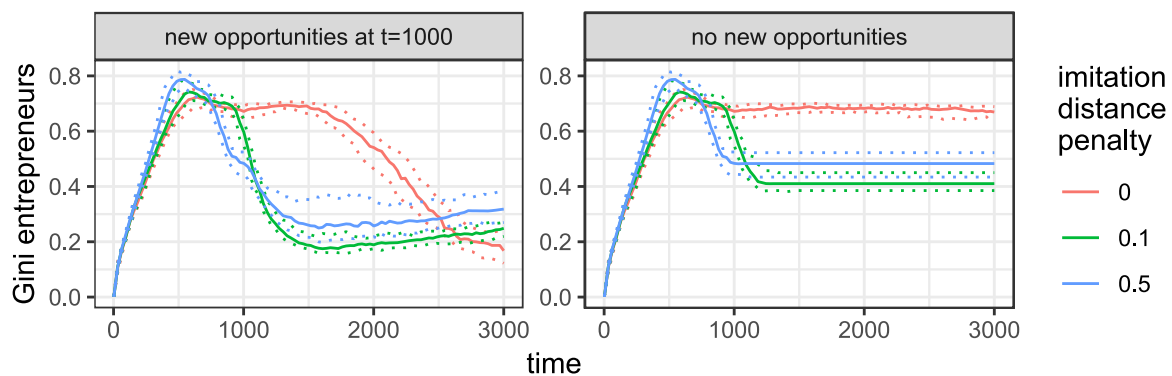


Figure 13: Gini index of combined market share

3.5 Policy scenarios

In this subsection, I am conducting a policy scenario analysis to investigate how a change in the model's other parameters affect my results. In order to save space and because the differences between an imitation distance penalty parameter of 0.1 and 0.5 do not qualitatively change the results, I only show the results for the parameter values 0 and 0.1. I also concentrate on those model outputs that exhibit visible differences between the parameter settings.

3.5.1 An increase in the capability to innovate (Mark II engine)

We can increase the innovative capacities of firms by varying the parameter ψ^{IN} , which influences the probability of inventing successfully. As fig. 14 shows, such an increase decreases inequality.

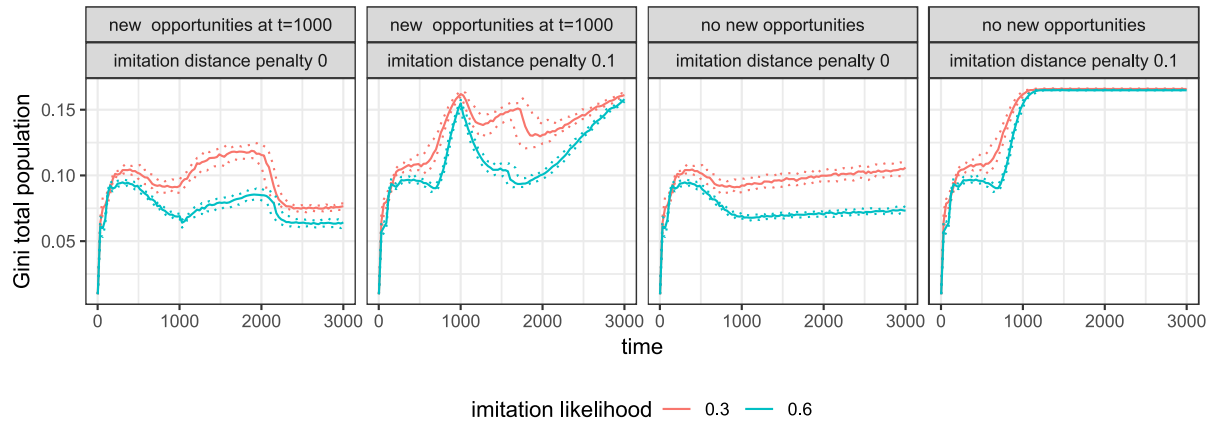


Figure 14: Varying the imitation likelihood

This result is driven by the fact that an increase in ψ^{IN} decreases the marginal probability of a successful invention added by one additional unit of labor employed for R&D and thus favors smaller firms. Therefore, market concentration is lower and thus, by extension, inequality is lower and employment and the wage share are higher.

3.5.2 An increase in the standard deviation of the productivity change by inventions

Another parameter which is important in modelling the Mark II engine is the standard deviation of the labor productivity change offered by an invention σ . While this does not affect the expected value of an *invention*, it does change the expected value of an *innovation*, since only inventions that increase labor productivity are actually selected by firms.

While such an increase trivially is beneficial to growth, it also increases inequality. Fig. 15 shows that this increase can be substantial, depending on the parameter settings. More specifically, raising σ increases both average productivity growth as well as industry concentration, the latter of which is connected to the well-known side-effects studied before (i.e. a falling labor share, higher markups, lower employment etc.).

Growth, Concentration and Inequality in a Unified Schumpeter Mark I + II Model

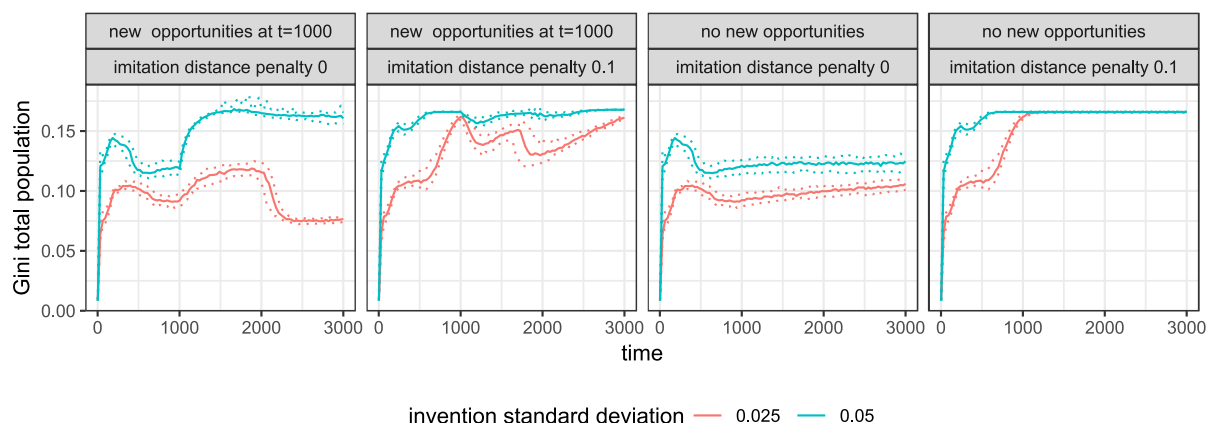


Figure 15: Impact of an increase in the invention standard deviation σ on inequality

The effect on real wages are non-trivial, since they are decreased by the fall in the labor share and increased by growth. However, fig. 16 shows that the growth effect clearly prevails in these scenarios.

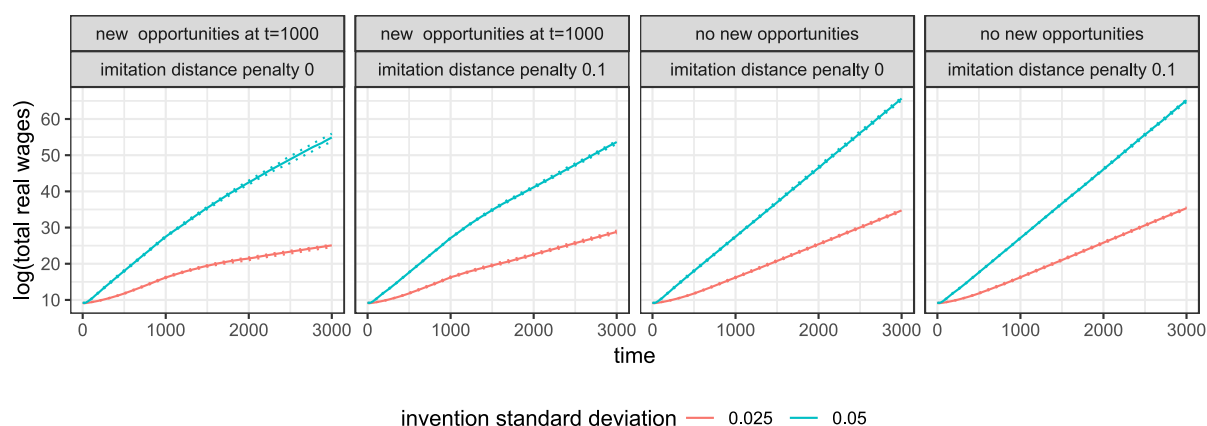


Figure 16: Impact of an increase in the invention standard deviation σ on real wages

3.5.3 Increase in the R&D propensity

An increase in the R&D propensity ν strengthens the Schumpeter Mark II engine, as it increases the probability of a successful imitation and/or invention. At the same time, it also increases employment and thus the wage share. Followingly, we can see from fig. 17 and 18 that the impact on inequality and concentration can differ: While market concentration may increase (due to a stronger Mark II engine), total inequality generally decreases (due to a higher labor share).

Growth, Concentration and Inequality in a Unified Schumpeter Mark I + II Model

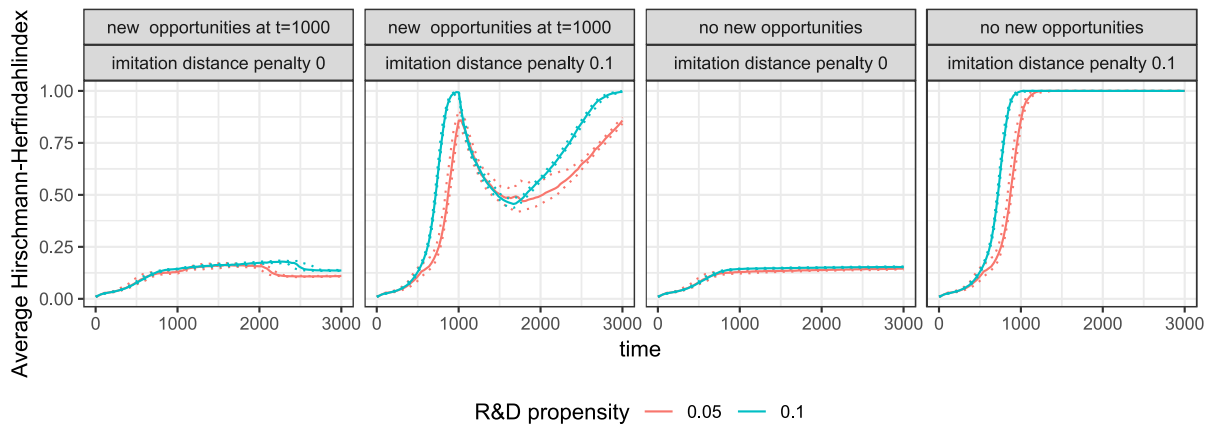


Figure 17: Average HHI for an increase in the R&D propensity

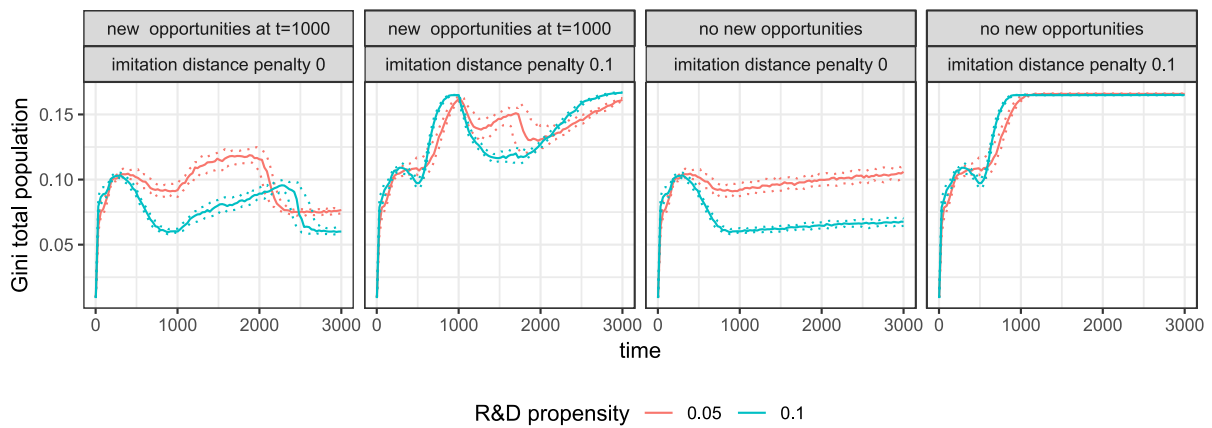


Figure 18: Gini of the total population for an increase in the R&D propensity

3.5.5 An increase in the savings rate

An increase in the savings rate implies that a) (successful) entrepreneurs are able to enter new industries more quickly and b) aggregate nominal demand is, *ceteris paribus*, lower. In general, this causes increased market concentration, except for the scenario in which there does not exist an imitation distance penalty and no new technological opportunities, where we observe a slight long-run decrease.

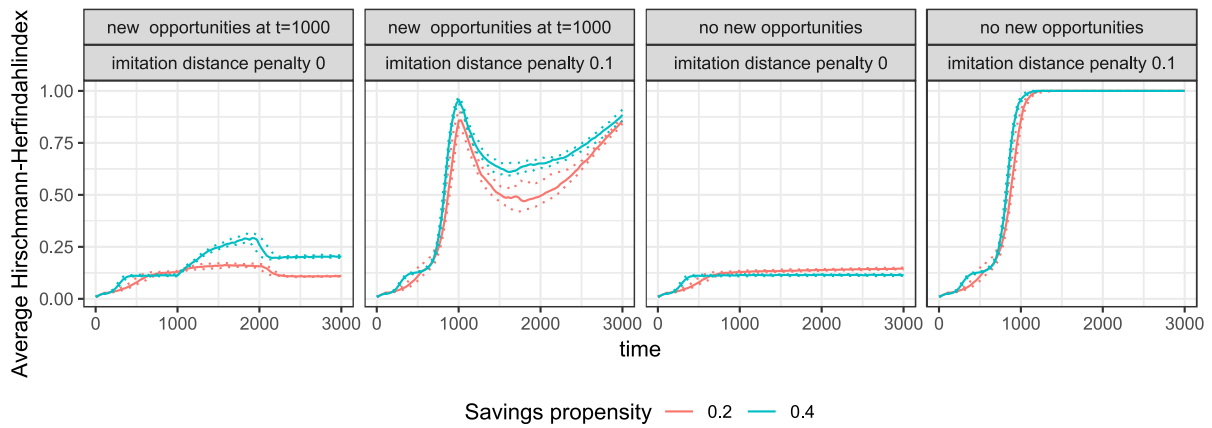


Figure 19: Average market concentration (Hirschmann-Herfindahl index) for an increase in the savings rate

3.5.6 Higher imitation capability

Increasing the imitation capability parameter causes a decrease in market concentration, even though this effect is only temporary if an imitation distance penalty exists. It is further beneficial for growth, i.e. increases total output, as long as no imitation penalty exists.

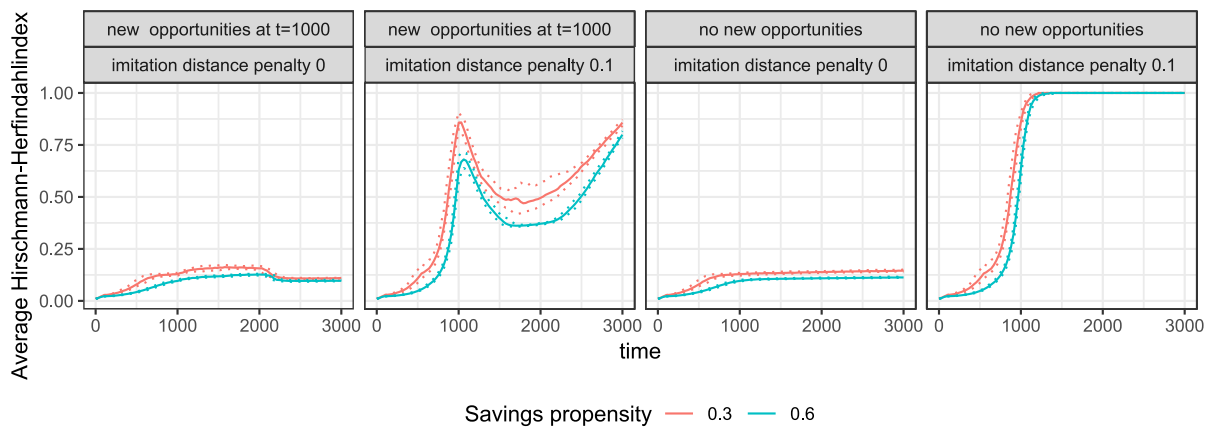


Figure 20: Average market concentration for a higher savings propensity

3.5.7 No imitation at the firm-level

If, in contrast, we assume that firms devote all of their R&D efforts to invention and none to invention, e.g. because imitation is prohibited (as e.g. in Terranova and Turvo 2021), we observe a strong increase

in market concentration and inequality, leading to complete market concentration in the steady state for any scenario (see fig. 21).

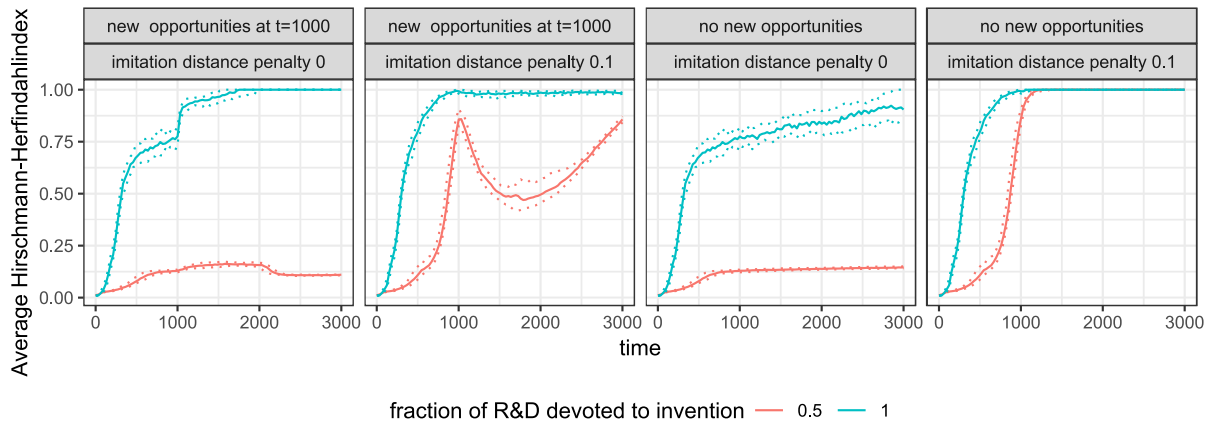


Figure 21: Market concentration if firm-level imitation is possible/impossible

Notably, in this case a wave of radical innovation *cannot* decrease inequality, even if we still allow for imitation by entrepreneurs, i.e. market entry of new firms, and assume that there is no imitation distance penalty since the entrepreneurs figuratively engage in a *Battle Royale* that only a single entrepreneur can survive in the long run (see fig. 22).

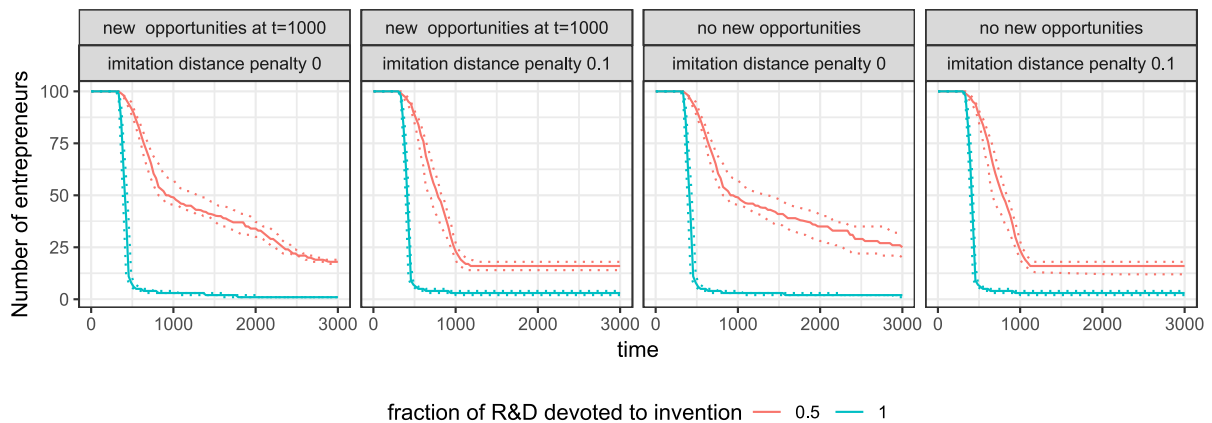


Figure 22: Number of entrepreneurs if firm-level imitation is possible/impossible

3.5.8 A larger technology push

What if the number of technological opportunities added at $t=1000$ increases? In this case, the number of industries continues its growth path until all technological opportunities are exploited (see fig. 23). Notably, this change affects the trajectory of market concentration, as the importance of the “early

phase” of the Schumpeter Mark I engine is prolonged, in which market concentration is high enough to generate sizable surplus profits, but not high enough to incentivize further market entry in the presence of the radical innovation alternative (see fig. 24).

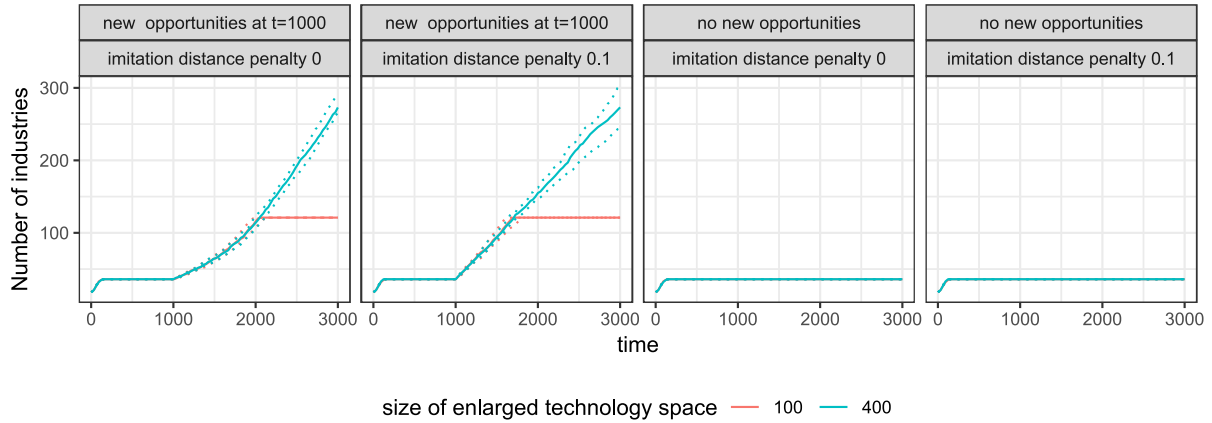


Figure 23: Number of industries for different sizes of enlarged technology space

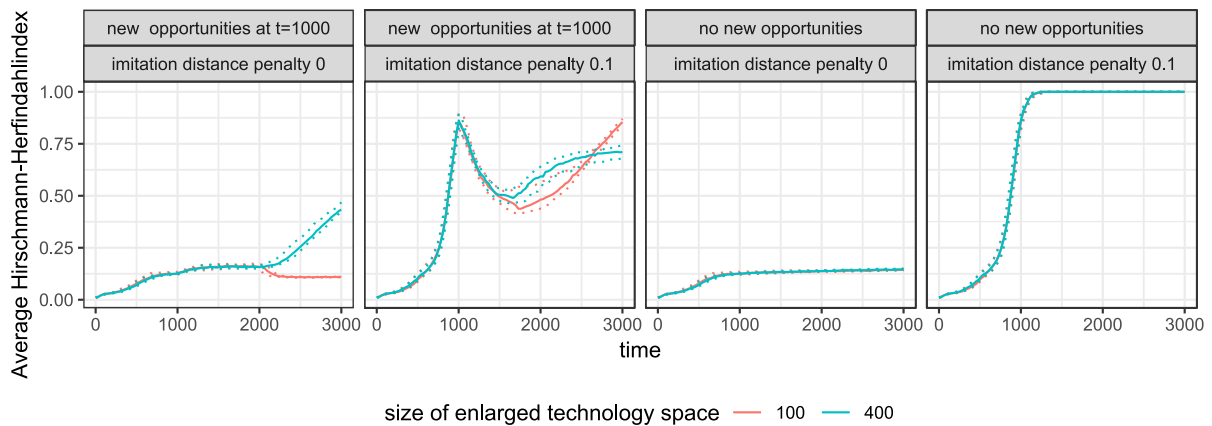


Figure 24: Average HHI for different sizes of enlarged technology space

3.5.9 Lower chance to successfully conduct a radical innovation

Lowering the chance to successfully conduct a radical innovation increases the length of the cycle triggered by the arrival of new technological opportunities (see fig. 25).

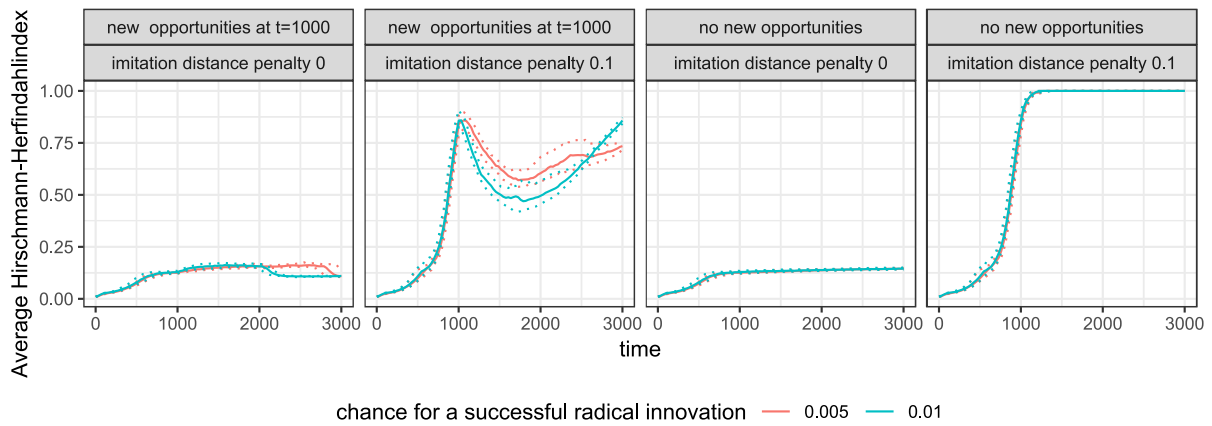


Figure 25: Average HHI for different chances to successfully conduct a radical innovation

3.5.10 More initial market concentration

In this scenario, I decrease the initial number of entrepreneurs. While the effect on inequality in the steady state is negligible, a temporary counterintuitive effect is possible, namely that an increase in initial market concentration causes a decrease in inequality in the medium run (see fig. 26). This effect is driven by the fact that the initial number of entrepreneurs in both scenarios (50 and 100) is unsustainable as the majority is not able to catch up with those who gain an early edge in the competition due to successes in R&D. Thus, many entrepreneurs have to go bankrupt before the system can reach a steady state, but a stronger initial position increases the likelihood of surviving the “shake-out phase” in the early timesteps for each firm. These results are almost unaffected if we assume that the total number of entrepreneurs is the same as in the baseline scenario (100), but the number of firms in each industry is set to 50.

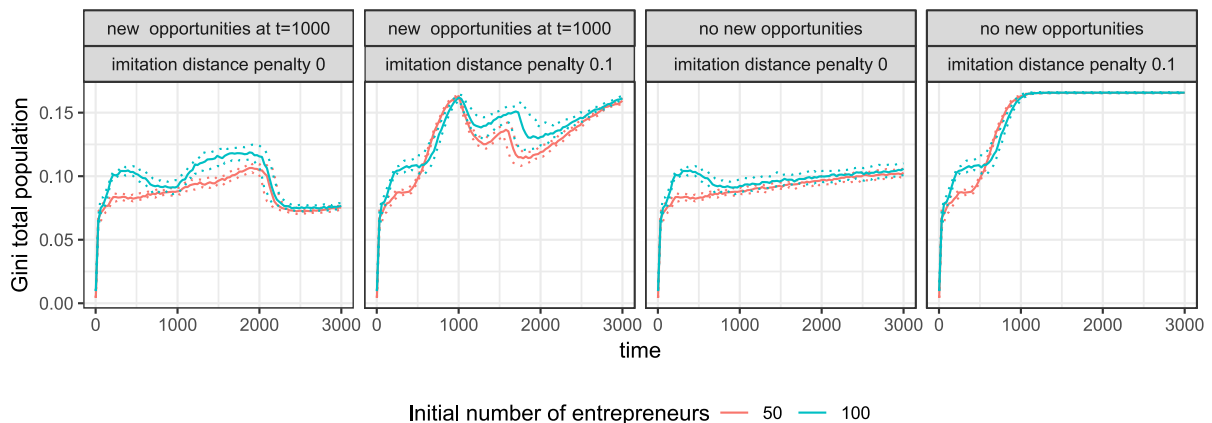


Figure 26: Gini of the total population for a lower initial number of entrepreneurs.

3.5.11 More workers

Increasing the initial number of workers strengthens both the Mark I engine, as labor is now relatively cheaper and entrepreneurs can thus become active sooner, and the Mark II engine, more labor is invested in R&D activities. This has an unequivocally positive effect on the output per capita (see fig. 27). The impact on market concentration is less trivial due to the counteracting forces of Mark I and II, but the impact on the steady state level of concentration is very low (see fig. 28).

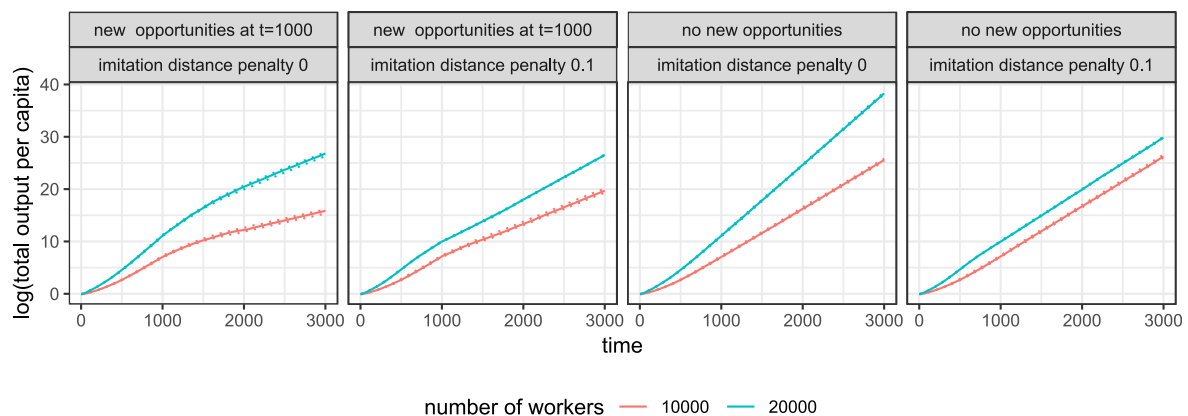


Figure 27: Log output per capita for a varying number of workers

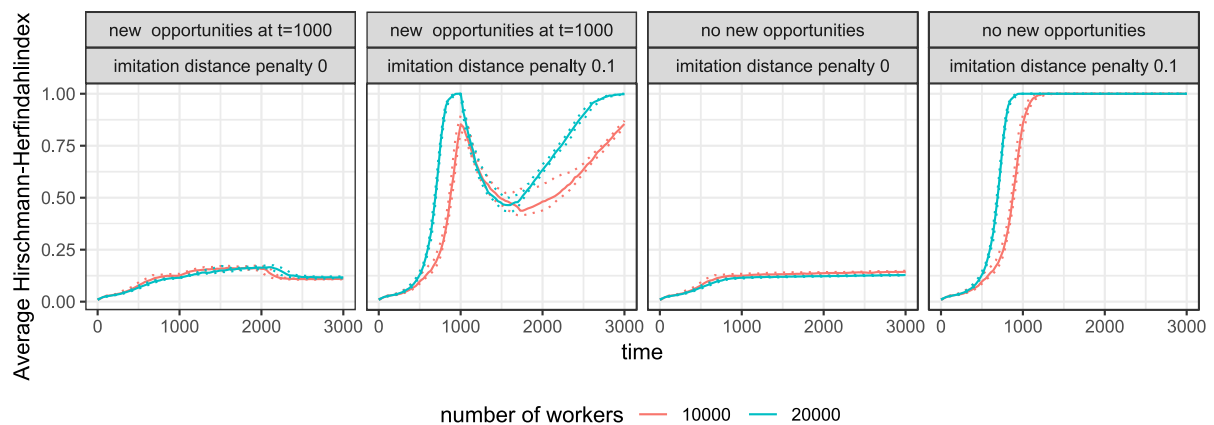


Figure 28: Market concentration for a varying initial number of workers

3.5.12 Increasing the target rate of profit

Increasing the target rate of profit triggers counteractive tendencies: On the one hand, it increases the profits of monopolists, thus increasing inequality. On the one hand, this effect increases the incentives

to enter a market dominated by a monopolist, thus decreasing the level of market concentration, which decreases inequality (see fig. 29).

Fig. 30 shows that the effect which increases inequality prevails, if an imitation distance penalty exists. If such a penalty doesn't exist, an increase in the target rate of profit does not have a significant effect, as winner-take-all markets cannot exist in the long-run. Fig. 31 finally shows that increasing the target rate of profit also has an adverse effect on output, which suggests that limiting the profitability of monopolies has an unequivocally beneficial effect on inequality and growth within this model.

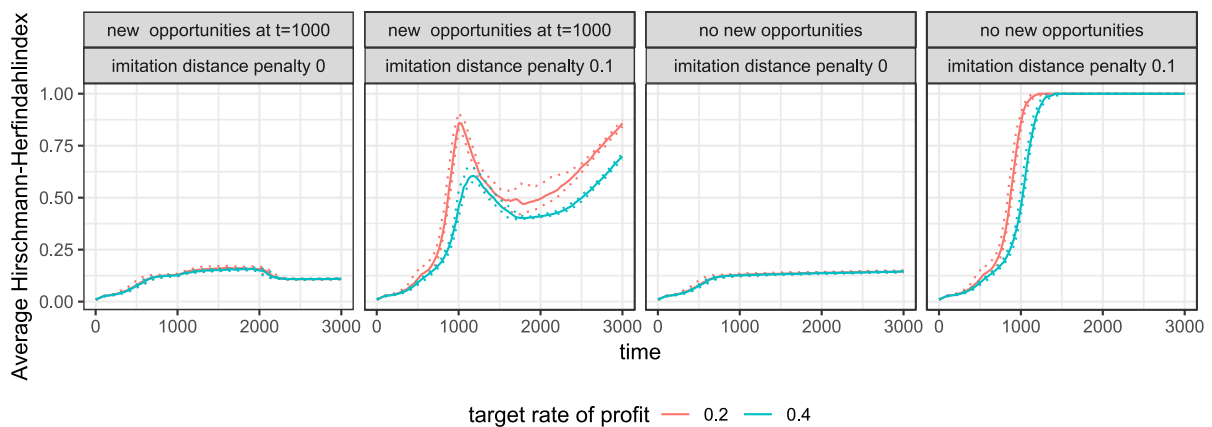


Figure 29: Market concentration for a varying target rate of profit

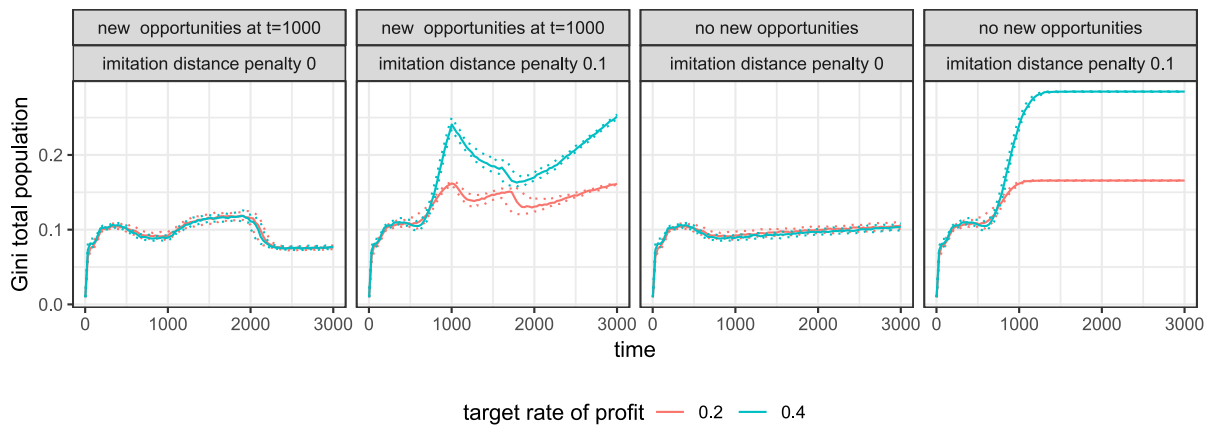


Figure 30: Income Gini for a varying target rate of profit

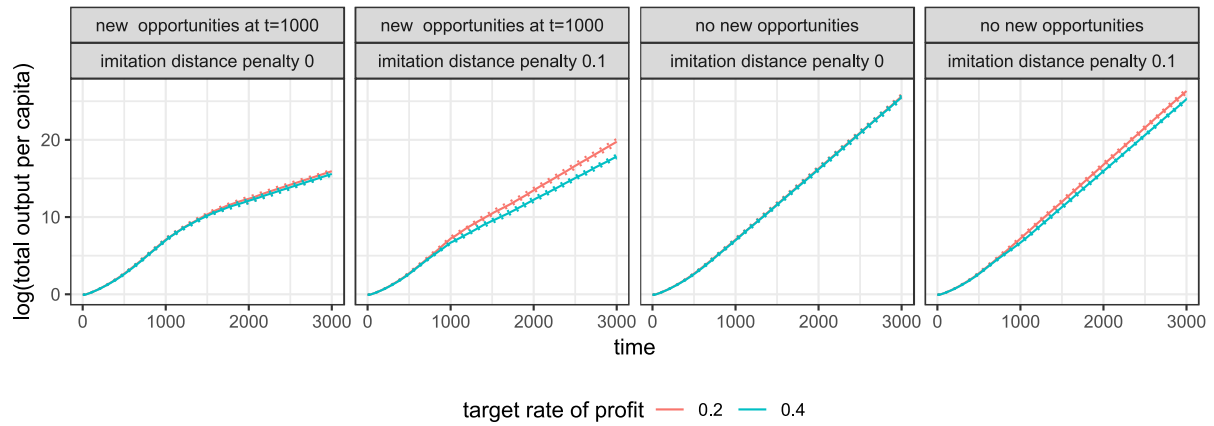


Figure 31: Total output for a varying target rate of profit

4 Conclusion

In this paper, I developed a simple agent-based model that incorporates key features of the so-called Schumpeter Mark I model and the Schumpeter Mark II model. My unified Schumpeter Mark I + II model allows for endogenous technological change in two dimensions: a) the number of industries, b) the firm-specific productivity. Despite its simplicity, this model is able to reproduce a large number of stylized facts regarding the evolution of capitalism in general and the industry life-cycle, the evolution of aggregate growth and inequality, as well as “declining business dynamism” (Ufuk and Akcigit 2021) since the 1980s in particular.

I then conducted an extensive analysis of the parameters governing the birth and evolution of industries in my model. This paper offers an explanation for the rising inequality and “declining business dynamism” that can be empirically tested: Namely, that these tendencies are driven by the ability of industry leaders to distance themselves from their competitors, which leads to an increase in market concentration within industries and to the rise of “superstar firms” (Autor et al. 2020). Second, this dynamic was not offset (enough) by the creation of new industries which would be easier to enter.

Naturally, the increase in inequality since the 1980s has also been driven by other economic, social and political factors which are beyond the scope of my current analysis. Nevertheless, the new technologies, whose importance has risen dramatically since the 1980s, seem to offer some support for the explanation brought forward in this paper. Both the production of hardware and software are highly concentrated among a few firms for each product. The same holds for related technologies such as mobile phones and their operating systems. The apparent reasons for this strong market concentration are manifold and are not explicitly captured in my model in order to preserve both its

simplicity and its generality. In order to name just three crucial ones: the cost structure of software (i.e. high sunk costs and extremely low marginal costs), learning effects (stemming from, e.g., the development of similar products), as well as network-effects (e.g. platform compatibility and adoption of two-sided platforms).

Within this apparent general trend, however, there are also counter-examples which show that the evolution of industries can facilitate increased competition at a certain stage of their development. For instance, the rise of “indie games” arguably contributed to a decrease in concentration of the market for computer games in recent years. Three reasons seem to be particularly important to explain this trend: first, the role of crowdfunding in enabling the development of products that could not have been financed with traditional means. Second, the costs of distributing a computer game decreased dramatically due to the availability of broad band internet. This enables small producers to easily sell their products to a world-wide audience. Third, the increase in the market size for computer games have allowed to increase the yearly number of games that could be developed profitably.

These countervailing mechanisms are currently not captured in my model, but seem to open up promising avenues for further research based on more complex mechanisms capturing finance, inter-industrial dependencies and relations, as well as dynamic market sizes. In particular, such research could complement the important advances by e.g. Saviotti and Pyka (2008), Ciarli and Lorentz (2010) and Dosi et al. (2021b) regarding the market size for each industry.

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References

- Acemoglu, D. (1998). Why do new technologies complement skills? Directed technical change and wage inequality. *The Quarterly Journal of Economics*, 113(4), 1055–1089.
- Acemoglu, D. (2002). Directed technical change. *Review of Economic Studies*, 69(4), 781–809.
- Acemoglu, D., & Robinson, J. A. (2002). The political economy of the Kuznets curve. *Review of development economics*, 6(2), 183-203.
- Aghion, P., & Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60, 323-351.
- Aghion, P. (2002). Schumpeterian growth theory and the dynamics of income inequality. *Econometrica*, 70(3), 855-882.

- Aghion, P., Akcigit, U., Bergeaud, A., Blundell, R., & Hémous, D. (2019). Innovation and top income inequality. *The Review of Economic Studies*, 86(1), 1-45.
- Akcigit, Ufuk and Ates, Sina (2021): Ten Facts on Declining Business Dynamism and Lessons from Endogenous Growth Theory, *American Economic Journal: Macroeconomics* 13(1), 257-298.
- Applegate, J. M., & Janssen, M. A. (2020). Job Mobility and Wealth Inequality. *Computational Economics*, Online First, 1-25.
- Assenza, T., Delli Gatti, D., & Grazzini, J. (2015). Emergent dynamics of a macroeconomic agent based model with capital and credit. *Journal of Economic Dynamics and Control*, 50, 5-28.
- Autor, D. H., Katz, L. F., & Krueger, A. B. (1998). Computing inequality: Have computers changed the labor market? *The Quarterly Journal of Economics*, 113(4), 1169–1213.
- Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4), 1279–1333.
- Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2017). Concentrating on the Fall of the Labor Share. *American Economic Review*, 107(5), 180-85.
- Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, 135(2), 645-709.
- Bloom, N., Schankerman, M., & Van Reenen, J. (2013). Identifying technology spillovers and product market rivalry. *Econometrica*, 81(4), 1347-1393.
- Bordot, F., Lorentz A. (2021). Automation and labor market polarization in an evolutionary model with heterogeneous workers. *LEM Working Paper Series 2021/32*.
- Caiani, A., Godin, A., Caverzasi, E., Gallegati, M., Kinsella, S., & Stiglitz, J. E. (2016). Agent based-stock flow consistent macroeconomics: Towards a benchmark model. *Journal of Economic Dynamics and Control*, 69, 375-408.
- Caiani, A., Russo, A., & Gallegati, M. (2019). Does inequality hamper innovation and growth? An AB-SFC analysis. *Journal of Evolutionary Economics*, 29(1), 177-228.
- Caiani, A., Russo, A., & Gallegati, M. (2020). Are higher wages good for business? An assessment under alternative innovation and investment scenarios. *Macroeconomic Dynamics*, 24(1), 191-230.
- Carvalho, L., & Di Guilmi, C. (2020). Technological unemployment and income inequality: a stock-flow consistent agent-based approach. *Journal of Evolutionary Economics*, 30(1), 39-73.
- Cengiz, D., Dube, A., Lindner, A., & Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics*, 134(3), 1405-1454.
- Ciarli, T., & Lorentz, A. (2010, June). Product variety and changes in consumption patterns: The effects of structural change on growth. In *13th ISS Conference, Aalborg*.
- Dawid, H. (2006). Agent-based models of innovation and technological change. *Handbook of computational economics*, 2, 1235-1272.
- Dawid, H., Gemkow, S., Harting, P., Van der Hoog, S., & Neugart, M. (2012). The eurace@ unibi model: An agent-based macroeconomic model for economic policy analysis. *Bielefeld Working Papers in Economics and Management No. 05-2012*.
- Dawid, H., & Gemkow, S. (2014). How do social networks contribute to wage inequality? Insights from an agent-based analysis. *Industrial and Corporate Change*, 23(5), 1171-1200.

- Dawid, H., Harting, P., & Neugart, M. (2021). The role of (de-) centralized wage setting for industry dynamics and economic growth: An agent-based analysis with the euraice@ unibi model. In *Dynamic Analysis in Complex Economic Environments* (pp. 205-230). Springer.
- Dawid, H., & Hepp, J. (2021). Distributional effects of technological regime changes: Hysteresis, concentration and inequality dynamics. *Bielefeld Working Papers in Economics and Management No. 09-2021*.
- De Loecker, J., Eeckhout, J., & Unger, G. (2020). The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics*, 135(2), 561-644.
- Derenoncourt, E., & Montialoux, C. (2021). Minimum wages and racial inequality. *The Quarterly Journal of Economics*, 136(1), 169-228.
- Dinlersoz, E. M., & MacDonald, G. (2009). The industry life-cycle of the size distribution of firms. *Review of Economic Dynamics*, 12(4), 648-667.
- Dosi, G., Fagiolo, G., & Roventini, A. (2010). Schumpeter meeting Keynes: A policy-friendly model of endogenous growth and business cycles. *Journal of Economic Dynamics and Control*, 34(9), 1748-1767.
- Dosi, G., Pereira, M. C., Roventini, A., & Virgillito, M. E. (2017). When more flexibility yields more fragility: The microfoundations of Keynesian aggregate unemployment. *Journal of Economic Dynamics and Control*, 81, 162-186.
- Dosi, G., Pereira, M. C., Roventini, A., & Virgillito, M. E. (2018). The effects of labour market reforms upon unemployment and income inequalities: an agent-based model. *Socio-Economic Review*, 16(4), 687-720.
- Dosi, G., Freeman, R. B., Pereira, M. C., Roventini, A., & Virgillito, M. E. (2021a). The impact of deunionization on the growth and dispersion of productivity and pay. *Industrial and Corporate Change*, 30(2), 377-408.
- Dosi, G., Pereira, M. C., Roventini, A., & Virgillito, M. E. (2021b). *Technological paradigms, labour creation and destruction in a multi-sector agent-based model* (No. 2021/17). Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy.
- Dustmann, C., Lindner, A., Schönberg, U., Umkehrer, M., & Vom Berge, P. (2021). Reallocation effects of the minimum wage. *The Quarterly Journal of Economics*, forthcoming.
- Fanti, L. (2021). 'Kaldor Facts' and the decline of Wage Share: An agent based-stock flow consistent model of induced technical change along Classical and Keynesian lines. *Journal of Evolutionary Economics*, 31(2), 379-415.
- Farber, H. S., Herbst, D., Kuziemko, I., & Naidu, S. (2021). Unions and inequality over the twentieth century: New evidence from survey data. *The Quarterly Journal of Economics*, 136(3), 1325-1385.
- Fierro, L. E., Caiani, A., & Russo, A. (2021). *Automation, job polarisation, and structural change* Working Papers 2021/09, Economics Department, Universitat Jaume I, Castellón (Spain).
- Freeman, C. (1982). *The Economics of Industrial Innovation*. Second Edition. London: Frances Pinter (Publishers).
- Gemkow, S., & Neugart, M. (2011). Referral hiring, endogenous social networks, and inequality: an agent-based analysis. *Journal of Evolutionary Economics*, 21(4), 703-719.
- Gort, M., & Klepper, S. (1982). Time paths in the diffusion of product innovations. *The Economic Journal*, 92(367), 630-653.
- Gräbner, C., & Hornykewycz, A. (2021). Capability accumulation and product innovation: an agent-based perspective. *Journal of Evolutionary Economics*, 1-35.

- Jones, C. I., & Kim, J. (2018). A Schumpeterian model of top income inequality. *Journal of Political Economy*, 126(5), 1785-1826.
- Klepper, S., & Graddy, E. (1990). The evolution of new industries and the determinants of market structure. *The RAND Journal of Economics*, 27-44.
- Kuznets, S. (1955). Economic growth and income inequality. *The American economic review*, 45(1), 1-28.
- Liao, C. T. (2020). Laggards imitate, leaders innovate: the heterogeneous productivity effect of imitation versus innovation. *Industrial and Corporate Change*, 29(2), 375-394.
- Marx, K. (1890). *Das Kapital: Kritik der Politischen Ökonomie (1. Band)*. Hamburg: Verlag von Otto Meissner.
- Mellacher, P. (2020). COVID-Town: An Integrated Economic-Epidemiological Agent-based Model. *GSC Discussion Paper Series No. 23*.
- Mellacher, P., & Scheuer, T. (2021). Wage Inequality, Labor Market Polarization and Skill-Biased Technological Change: An Evolutionary (Agent-Based) Approach. *Computational Economics*, 58(2), 233-278.
- Nelson, R. R., & Winter, S. G. (1982). *An Evolutionary Theory of Economic Change*. Harvard University Press.
- Piketty, T. (2014). *Capital in the twenty-first century*, Cambridge Massachusetts: The Belknap Press of Harvard University Press.
- Piketty, T., & Saez, E. (2014). Inequality in the long run. *Science*, 344(6186), 838-843.
- R Core Team (2020). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>
- Reiter, O. (2019). *Declining business dynamism explained by an agent-based macro model*. Paper presented at the workshop "Agent-based economics" at the University of Graz.
- Rengs, B., & Scholz-Wäckerle, M. (2019). Consumption & class in evolutionary macroeconomics. *Journal of Evolutionary Economics*, 29(1), 229-263.
- Romer, P. M. (1990). Endogenous technological change. *Journal of political Economy*, 98(5, Part 2), S71-S102.
- Ricardo, David (1817). *On the Principles of Political Economy and Taxation*. London: John Murray
- Savin, I., & Egbertokun, A. (2016). Emergence of innovation networks from R&D cooperation with endogenous absorptive capacity. *Journal of Economic Dynamics and Control*, 64, 82-103.
- Saviotti, P. P., & Pyka, A. (2004a). Economic development by the creation of new sectors. *Journal of evolutionary economics*, 14(1), 1-35.
- Saviotti, P. P., & Pyka, A. (2004b). Economic development, qualitative change and employment creation. *Structural Change and Economic Dynamics*, 15(3), 265-287.
- Saviotti, P. P., & Pyka, A. (2008). Micro and macro dynamics: Industry life cycles, inter-sector coordination and aggregate growth. *Journal of Evolutionary Economics*, 18(2), 167-182.
- Schumpeter, J. A. (1911): *Theorie der wirtschaftlichen Entwicklung*, Leipzig: Duncker & Humblot.

- Schumpeter, J. A. (1934). *The theory of economic development*, Harvard University Press. Cambridge, MA.
- Schumpeter, J. A. (2003[1942]): *Capitalism, Socialism and Democracy*, London and New York: Routledge.
- Terranova, R., & Turco, E. M. (2021). Concentration, Stagnation and Inequality: An Agent-Based Approach. *ExSIDE Working Paper No. 38-2021*.
- Vallejos, H. A., Nutaro, J. J., & Perumalla, K. S. (2018). An agent-based model of the observed distribution of wealth in the United States. *Journal of Economic Interaction and Coordination*, 13(3), 641-656.
- Vermeulen, B., Kesselhut, J., Pyka, A., & Saviotti, P. P. (2018). The impact of automation on employment: just the usual structural change?. *Sustainability*, 10(5), 1661.
- Walraevens, B. (2021). Adam Smith's view of economic inequality. *Cambridge Journal of Economics*, 45(1), 209-224.
- Wersching, K. (2010). Schumpeterian competition, technological regimes and learning through knowledge spillover. *Journal of Economic Behavior & Organization*, 75(3), 482-493.
- Wickham H (2016). *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York
- Wilensky, U. (1999). NetLogo. <http://ccl.northwestern.edu/netlogo/>. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.
- Wolf, S., Fürst, S., Mandel, A., Lass, W., Lincke, D., Pablo-Marti, F., & Jaeger, C. (2013). A multi-agent model of several economic regions. *Environmental modelling & software*, 44, 25-43.