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Abstract

The role of the patent system in the pharmaceutical sector is highly debated also due to its strong public health implications. In this paper we develop an evolutionary, agent-based model of the pharmaceutical industry to explore the impact of different configurations of the patent system upon innovation and competition. The model is able to replicate the main stylized facts of the drug industry as emergent properties. We perform policy experiments to assess the impact of different IPR regimes changing the breadth and length of patents. Results suggest that enlarging the extent and duration of patents yields adverse effects in terms of innovation outcomes, as well as of market competition and consumer welfare. Such general conclusions hold even if one takes into account the possible positive effects on R&D intensity and information disclosure triggered by patents.

Keywords: Innovation, Intellectual property rights, Market power, Pharmaceutical sector, Agent-based models

JEL classification: L10 · L65 · O30 · O34 · C63

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1 Introduction

In this paper we develop an evolutionary, agent-based model to study the role of patents on innovation, technological diffusion and industry dynamics, with explicit reference to the pharmaceutical sector.

The structure of the contemporary patent system led a large number of scholars to flag its deep disfunctionalities (Jaffe and Lerner, 2004; Stiglitz, 2007; Bessen et al., 2008; Boldrin et al., 2008; Cimoli et al., 2014). They concern both the effectiveness of patent rights in promoting innovation and an increasing awareness of the large inefficiencies and social costs imposed by extending the scope and stringency of protection (Heller and Eisenberg, 1998; Dosi et al., 2006; Baker et al., 2017). The ensuing policy debate on how to reform patent systems yielded various proposals for a radical institutional restructuring (see e.g. Dosi and Stiglitz, 2014; Baker et al., 2017; de Rassenfosse and Higham, 2021) or even the complete abolishment of intellectual property rights (Boldrin and Levine, 2013).

The discussion about patents is particularly relevant in the pharmaceutical sector (Orsenigo et al., 2006; Coriat and Orsenigo, 2014) and has gained even further attention in light of the current COVID-19 pandemics, which has again placed at the center of the public debate the role of innovation, its appropriability for private firms and the worldwide availability of vaccines during a health crises (Sampat and Shadlen, 2021; Dosi, 2021).

The discovery and development of new drugs is often depicted as a domain requiring patent protection due to the high R&D costs and the purported relative ease of product imitation (not surprisingly this view is supported especially by the industry itself, see e.g. the latest takes by the PhRMA and EFPIA associations)[1]. Proponents of this view point to the long, costly and highly uncertain search processes preceeding the discovery of new drugs as motivations for strong patent protection. In this perspective, the patent system, is essential in order to protect innovative firms from imitators that may enter the market with relatively smaller investments (Scherer, 2010).

The actual uncertainty and costs associated with the discovery of new drugs is of course an empirical matter. What we know is that the numbers often flagged are vastly inflated (Angell, 2005). Moreover, the pharmaceutical sector is also characterized by large public funding of basic research (as well as on government subsidies) and, on the demand side, by the key role of public demand stemming from national healthcare systems. In this respect, patents make the public paying twice for medical innovations: first by financing research and taking the risk in the early stage of product discovery[2] and, second, via public procure-

[1]See for instance: https://innovation.org/about-us/commitment/innovation-fragility/world-ip-day-intellectual-property-protections-spur-innovation;
https://www.efpia.eu/about-medicines/development-of-medicines/intellectual-property.

[2]For instance, Cleary et al. (2018) finds that in the period 2010-2016 all the New Chemical Entities (NCE)

ment of drugs payed at monopolistic prices (Lazonick and Mazzucato, 2013; Mazzucato et al., 2020). In fact, as discussed in Dosi (2021), there is a long-term decrease in private R&D investment in basic science (Arora et al., 2018). Nowadays, most pharmaceutical firms are likely to lack the basic internal knowledge in key areas such as vaccine development (so among the newly approved chemical entities since 2000, less than 6% regarded antibiotics or antivirals Walker, 2017).[3]

The patent system is also perversely affecting the direction of innovation towards finding treatments for diseases that guarantee high returns in the short term, while neglecting more risky or less remunerative research investments (e.g. diseases affecting poor countries, Lanjouw and Cockburn, 2001; Kremer, 2002; Orsenigo et al., 2006; Budish et al., 2015).[4]

Not too surprisingly, many studies based on firm surveys found that patents are considered by R&D managers as an essential tool to reap the benefits of innovation (Mansfield et al., 1981; Mansfield, 1986; Levin et al., 1987; Cohen et al., 2002). However, this is a totally different issue from whether such monopolistic profits have been necessary conditions for sustained rates of innovation. Historically, sustained rates of innovation occurred under regimes of loose or non-existent IPR, with profits stemming from innovative lead times, and complementary assets such as manufacturing capabilities (Coriat and Orsenigo, 2014; Dosi et al., 2021). Indeed the secular history of the pharmaceutical industry shows that patent protection was not necessary for the whole flow of major pharmaceutical innovations: see the fascinating reconstruction in Sneader (2005). A striking example is represented by the penicillin, which after being discovered in the UK, was industrialized in the US under the guidance of the Federal Office of Scientific Research and Development, which retained all patents (Best and Bradley, 2020; Gross and Sampat, 2021).

Dosi et al. (2021) report evidence on the long-term trends in patenting activities from pharmaceutical firms, suggesting that patents act as legal barriers protecting intellectual monopolies rather than being an incentive to innovative efforts. The foregoing account, in our view, summarizes the first order role of IPR in terms of rates and directions of innovative activities. One may also take a finer econometric look exploiting inter-country or inter-temporal differences in IPR protection and try to identify the effects of strengthening (or relaxing) patent regimes on different dimensions of innovation: even at this level the evidence remains hardly conclusive.[5]

approved by the Federal Drug Administration (FDA) received public funding, to different degrees, by the National Institutes of Health (NIH).

[3]In fact, big pharma's expenditure in basic R&D has been at low levels in the last decades (Light and Lexchin, 2005).

[4]In a recent work, Budish et al. (2016) find that fixed patent duration may distort research investment towards short-term projects in areas with shorter clinical trials and commercialization lags.

[5]Qian (2007) presents a cross-country study for countries that established patent laws for drugs during the 1978-2002 and finds no substantial effects upon domestic measures of innovation. Arora et al. (2008) use survey data for the US manufacturing sector and mainly find positive profit and R&D premiums in pharmaceuticals

From the viewpoint of theoretical modelling, to the best of our knowledge, there are no models tailored to the pharmaceutical industry that extensively explore the role of patents, with the partial exception of the pharma history-friendly model by Malerba and Orsenigo (2002) and Garavaglia et al. (2013), modelling the aforementioned empirical evidence.[6]

In this work, we fill this gap by developing a novel agent-based model of the drug industry, in order to study the impact of different degrees of patent protection upon innovation and sectoral performances. This is rooted in a long tradition of evolutionary simulation models of firm dynamics (Silverberg et al., 1988; Dosi et al., 1995; Winter et al., 2000, 2003; Dosi et al., 2016) and shares some similarities with history-friendly models (Malerba et al., 1999, 2001; Landini et al., 2017; Landini and Malerba, 2017), particularly the ones already mentioned on the pharmaceutical industry (Malerba and Orsenigo, 2002; Garavaglia et al., 2013).[7]

The model embeds an artificial industry populated by firms that compete in different submarkets corresponding to various therapeutic categories (e.g. analgesics, antibiotics). Firms invest in R&D in order to develop new products and gain market shares. Innovation may occur locally, in the form of quality improvements of the current drug submarket, or may result in product diversification as firms branch into other existing submarkets. Moreover, in rare cases, firm may discover a new submarket and enter in an unexplored therapeutic category. Innovations are protected by patents that allow innovative companies to exclude competitors from areas of the product space surrounding their newly discovered drugs. The patent system is characterized by its breadth, which determines the extent of the infringement area, and by its length, i.e. the duration of protection. The imitation of products whose patents have expired is relatively easier thanks to the disclosure of information promoted by the patent system.

The parameters of the model are chosen in line with the key observable variables. The model in its baseline and in all its variants generates, as emergent properties, the broad range of empirical regularities of the pharmaceutical industry (Bottazzi et al., 2001; Bottazzi and Secchi, 2005; Scherer, 2010; Malerba and Orsenigo, 2015). More specifically, we are

associated to patented products. Williams (2013) and Sampat and Williams (2019) document negative effects on follow-on innovations associated to patented products.

[6]Evolutionary models have investigated the effects of intellectual property rights in the context of either complex product industries (Vallée and Yıldızoglu, 2007; Marengo et al., 2012) or in a science-based technological regime (Winter, 1993). They find adverse effects on innovation, product quality and consumer welfare associated to patents. Here we cannot discuss at any length the relationships between the evolutionary model of this paper and those of the "equilibrium" genre, which in fact postulate a positive relations, possibly of a non-linear form, between patent protection and innovation (cf. Fudenberg et al., 1983; Acemoglu and Akcigit, 2012; Aghion et al., 2015, among quite a few others).

[7]Differently from history-friendly models, our work is not focused on matching broad historical trends. Also, they have not been adopted to study the role of patents. Our strategy, instead, is to calibrate the model in order to replicate current statistical regularities of the industry and, then, to run counterfactual policy experiments imposing different patent regimes.

able to replicate a set of stylized facts including: (i) the increasing size of the industry and an increasing product variety; (ii) ubiquitous heterogeneity along various dimensions; (iii) the emergence of an "oligopolistic core" of leading firms; (iv) right-skewed firm size distributions; (iv) tent-shaped growth rates densities; (v) serial correlation in firm growth rates; (vi) positive relation between firm size and the number of active submarkets.

On the grounds of our empirically validated baseline, we then run different policy experiments allowing for various degrees of patent breadth and length to study their impact on innovation and industry dynamics. Our results suggest that a more stringent patent regime hampers innovation (i.e. higher number of blocked innovations and an overall decrease in product variety), while it increases market concentration and prices. In a nutshell, the model shows that strengthening the patent system restricts the exploration of technological opportunities and leads to a substantial fall in innovation rates and new drug discoveries. As second-order effects, tighter intellectual property rights favour the emergence of monopolistic firms dominating different submarkets with associated welfare losses for consumers. Finally, such negative impacts of patents hold also when we strengthen their possible positive effects on R&D intensity and information disclosure. Conversely, weaker IPRs can thus foster innovation, drug discoveries and competition in the pharmaceutical industry.

The remainder of the paper is organized as follows. In Section 2 we present the model. Results are reported and discussed in Section 3. Finally, Section 4 concludes.

2 The model

The model includes N firms (indexed by i) located in different parallel submarkets (indexed by j), each representing a different therapeutic area, along which they compete via the discovery and development of new products.[8] Submarkets emerge endogenously as a result of innovation activities and are modelled as bi-dimensional, open-ended product lattices with coordinates x and y being two discrete measures of product quality. Thus, a given product in the submarket j, produced by firm i, at time t can be described by the pair: $x^j_{i,t}, y^j_{i,t}$. At any point in time, firms are fully characterized by: (i) the location of their products in the product space (at maximum one product per submarket); (ii) R&D investments; (iii) prices; (iv) market demand and total sales.

The model features a patent system that guarantees innovative firms the right to exclude competitors from the area in the neighborhood of the newly discovered product.

[8] In the empirical literature, therapeutic markets are identified using different classification systems. They may based on clinical symptoms or on the combination between the organ on which drugs act and/or their therapeutic and chemical characteristics (Pammolli et al., 2011).

Patented products, after the expiration of patent rights, can be easily imitated as a result of information disclosure effects. Via both mechanisms, the patent system feeds back to the innovation process, affecting both its rate and direction, as well as the dynamics of market power and competition.

In the next sections we provide a detailed description of the model by presenting the sequence of events as well as the rules and equations regulating firm behaviour and market selection.

2.1 Timeline of events

Within each time step events proceed as follows:

1. Firms set their R&D expenditures and allocate them to different types of search activities following adaptive behaviours.

2. The innovation process takes place. Firms may: (i) discover new products (or copy existing ones) in a submarket where they are already active; (ii) branch into an existing submarket where they are not yet operating; (iii) discover a new submarket.

3. Intellectual property rights are at work: firms that moved into areas protected by a patent are forced to stick to their old products. Instead, if there is no violation, firms are allowed to patent the newly discovered product.

4. Market competition opens: firms set prices and sell their products. At the end of this process, firm-specific sales are computed in each submarket and profits are determined.

5. Entry and exit start: firms exit from submarkets when market shares are below a minimum threshold. A firm dies when leaving all the submarkets. Entrants replace dying firms.

2.2 R&D and innovation

Firms are assumed to invest a constant share (s^{RD}) of their past sales in R&D:[9]

$$RD_{i,t} = s^{RD}\ sales_{i,t-1}, \tag{1}$$

[9]The assumption of invariant R&D shares is common to several evolutionary models (see e.g. Chiaromonte and Dosi, 1993; Dosi et al., 2010) and is corroborated by an ample empirical evidence (see among many others Mansfield, 1968; Freeman, 1982, and the general discussion in Kay, 1979). Past sales of course correlate with market size, profits and, generally, cash flows. On firms' R&D decisions in the pharmaceutical sector see also Grabowski and Vernon (2000); Arora et al. (2009) and Dubois et al. (2015). We set the R&D share to 10% in line with the empirical data (see Section 3). In Section 3.3.1, we present policy experiments allowing firms to adjust their shares in response to incentives provided by the patent system.

where $s^{RD} \in (0,1)$. Firms perform three different search activities that broadly reflect the types of discoveries made by pharmaceutical companies: (A) they invest to improve the quality of their products, for instance, in order to achieve better therapeutic efficacy of their currently produced drugs; (B) they strive to branch into existing submarkets where they are not yet operating, i.e. they try to differentiate their portfolio of products towards different therapeutic areas; (C) finally, a share of research efforts is devoted to the discovery of new drugs for unmet therapeutic needs, resulting in the emergence of a totally new submarket. Accordingly, firms split their total R&D expenditure along these three search activities (labelled using letters A, B and C):

$$RD^{A}_{i,t} = s^{A} RD_{i,t}, \tag{2}$$

$$RD^{B}_{i,t} = s^{B} RD_{i,t}, \tag{3}$$

$$RD^{C}_{i,t} = (1 - s^{A} - s^{B}) RD_{i,t}, \tag{4}$$

where $s^{A}, s^{B} \in [0,1]$ and $(s^{A} + s^{B}) \leq 1$.

We model innovation as a two-step stochastic process. At each time period, a Bernoulli draw determines whether the firm is successful in one or more innovation activities. This step accounts for the inherent uncertainty encountered in the discovery and development of new drugs during both the pre-clinical and clinical phases. For instance, innovation failures may result either from lack of success in isolating chemical molecules in laboratory or from non-favourable evidence during clinical trials (Scherer, 2010).[10] Hence, the probability of being successful in introducing a new product is positively influenced by R&D expenditures:

$$p^{A}_{i,t} = pmax^{A}(1 - e^{-\theta^{A} RD^{A}_{i,t}}), \tag{5}$$

$$p^{B}_{i,t} = pmax^{B}(1 - e^{-\theta^{B} RD^{B}_{i,t}}), \tag{6}$$

$$p^{C}_{i,t} = pmax^{C}(1 - e^{-\theta^{C} RD^{C}_{i,t}}), \tag{7}$$

with $pmax^{A}, pmax^{B}, pmax^{C} \in (0,1)$ and $\theta^{A}, \theta^{B}, \theta^{C} > 0$. The exponential parameters (θ^{A}, θ^{B}, θ^{C}) account for industry-wide factors that positively affect innovation probabilities. They shall be interpreted as proxies of the quality of the innovation system underlying each type of innovation. Most importantly, these include public funding of basic science as well as other direct and indirect forms of government support which fundamentally shape firms' search capabilities and innovation success in the pharmaceutical industry.[11]

[10] DiMasi et al. (2003) document attrition rates in clinical trials respectively of 29% for Phase I, 56% for Phase II and 31% for Phase III. Pammolli et al. (2011) find increasing attrition rates over time across both pre-clinical and clinical phases for the period 1990-2004.

[11] In this version of the model we restrain from directly introducing the government sector. Therefore, the

Structural degrees of uncertainty associated to different innovation activities impose different upper bounds $pmax$ to each type of innovation. For instance, there is much more uncertainty involved in the discovery of drugs for untreated diseases (i.e. resulting in the emergence of new submarkets) than in achieving incremental quality enhancement in an already existing therapeutic area. For this reason, we assume that: $pmax^A \geq pmax^B > pmax^C$. Here firms are also assumed to invest less in more uncertain research activities, that is: $s^A \geq s^B > s^C$. An obvious extension of the model would involve the differentiation across types of firms, e.g. "radical explorers" vs. "imitators" and study the evolution of such an ecology of firms. And another one would be the formal account of the falling propensity of pharmaceutical firms to invest in uncertain radical search revealed by the evidence discussed above. We leave it to future refinements.

If a firm is successful in the first step, it will introduce a new product in the market. The second step of the innovation process determines the characteristics of the drugs, that is, the submarket (therapeutic field) and its coordinates in the product space (quality). In actual fact, this second stage ought to capture also the complex and partially random process of molecular screening that lies behind the discovery of new drugs and the determination of their therapeutic use and efficacy (Scherer, 2010).

Let us now discuss the second step of the process for each type of innovation.

Quality improvements within submarket (type A). The innovative firm will achieve quality enhancements in a given submarket either by developing new drugs or by imitating higher-quality products from competitors. First, it will randomly pick with uniform probability one of the submarkets where it already operates (let us label the selected submarket with j^*). Thus, the drug produced by the firm in that specific submarket at $t-1$ is characterized by the coordinates: $x^{j^*}_{i,t-1}, y^{j^*}_{i,t-1}$. Define the E as the set of existing goods (with higher overall quality) produced by competitors at $t-1$ in j^*. Also, define S as a search area in a neighborhood of $x^{j^*}_{i,t-1}, y^{j^*}_{i,t-1}$, where:

$$S = \{(a,b) \mid a+b > x^{j^*}_{i,t-1} + y^{j^*}_{i,t-1}; a+b \leq x^{j^*}_{i,t-1} + y^{j^*}_{i,t-1} + k^{j^*}_{i,t-1}\}. \tag{8}$$

The innovative firm will draw a new product belonging to the space $E \cup S$. Intuitively, the firm may explore a search area in a neighborhood of its product or may copy one of the existing products from competitors with higher quality.[12]

The extent of the search area is regulated by the firm-specific variable k which evolves

role of public universities, research labs and other public policies (other than the patent system) is accounted by the exogenous parameters. We leave for future extensions the explicit modelling of public actors, as well as the analysis of different government interventions.

[12]Similar search rules have been introduced in other evolutionary models of innovation (see e.g. Fagiolo and Dosi, 2003; Silverberg and Verspagen, 2005).

according to:

$$k_{i,t-1}^{j^*} = \frac{\hat{k}}{1 - e^{-\gamma_k (x_{i,t-1}^{j^*} + y_{i,t-1}^{j^*})}}, \tag{9}$$

with $\hat{k}, \gamma_k > 0$. The intuition is that the scope for larger quality improvements decreases for firms that are close to the frontier, that is, the higher are x and y the lower is the extent of the local search area explored by the firm. The parameter $\hat{k}$ regulates the dimension of the area as a proxy of technological opportunity for firms at the frontier, while γ_k influences the speed at which opportunities are exhausted as the frontier is approached (as such, both parameters can be seen as being affected by the pre-existing advances in basic science, for which public research plays a dominant role).

Finally, the draw of the new product in $E \cup S$ is modelled with a transition probability matrix. The probability to discover a product with coordinates (a, b) in $E \cup S$ is defined as:

$$\begin{aligned} Prob(a,b) &= \frac{d(a,b)}{\sum_{(h,g)\in E\cup S} d(h,g)}, \\ \text{where:} \quad d(h,g) &= \frac{1 + \gamma_1 expiredpat(h,g)}{1 + \gamma_0 (h + g - x_{i,t-1}^{j^*} - y_{i,t-1}^{j^*})}, \end{aligned} \tag{10}$$

where $\gamma_0, \gamma_1 \geq 0$ and $expiredpat(h, g)$ is an indicator function being 1 if there is an expired patent associated to the product (h, g).

Therefore, the probability associated to a potential new product inversely depends on its distance from the current product, that is, achieving radical quality jumps in a submarket is harder than introducing incremental enhancements. At the same time, products that have been patented and whose patent has already expired are more likely to be copied as a result of information disclosure effects, thus, accounting for the arrival of generic drugs.

If the foregoing process is successful, that is if the new drug is "better" than the previous one, the firm updates its coordinates in submarket j^* and replaces its old product.

Penetrating into other existing submarkets (type B). Firms might also enter in an existing submarket with a new drug and thus to diversify their product portfolio. Define J as the number of existing submarkets at $t - 1$. Then, for the would-be innovative firm, the probability of entering in submarket $a \in [1, J]$ is defined as:

$$\begin{aligned} Prob(a) &= \frac{d(a)}{\sum_{b\in[1,J]} d(b)}, \\ \text{where:} \quad d(b) &= \begin{cases} 1 + \Psi Nex(b) & \text{if the firm is not already present in } b \\ 0, & \text{otherwise ,} \end{cases} \end{aligned} \tag{11}$$

where $\Psi \geq 0$ and $Nex(b)$ is the number of products in b with an expired patent associated.

Hence, there is higher likelihood to enter submarkets that have a large number of products with expired patents, again, reflecting disclosure effects (mediated by the parameter Ψ). Finally, after picking the new submarket (let us label it with j^{NEW}), the firm will simply randomly draw a point in the space spanned by $[1, X_{t-1}^{j^{NEW}}]$ and $[1, Y_{t-1}^{j^{NEW}}]$, where $X_{t-1}^{j^{NEW}}$ and $Y_{t-1}^{j^{NEW}}$ represent the quality frontiers in submarket j^{NEW} at time $t-1$. The new product will be added to the set of products of the firm.

Discovery of new submarkets (type C). The innovation is radical and the firm will open a new submarket. This corresponds to a scenario where a firm finds a new drug in an unexplored therapeutic area. Define J as the number of existing submarkets at $t-1$, then the firm will open the new bi-dimensional space $J+1$. The initial product in this submarket will be randomly drawn in the area spanned by $[1, Xinit]$ and $[1, Yinit]$, where $Xinit$ and $Yinit$ characterize the initial dimension of each new submarket. The innovative firm will be the first mover and add the new product to its portfolio. In subsequent periods, second-movers will be allowed to join the new submarket (via branching, i.e. innovation type B).

2.3 The patent system

Patents grant the right to exclude competitors from moving into a neighboring area of the patented product. Given product coordinates x^j and y^j, the area of violation is defined as:

$$V = \{(a, b) \mid x^j - Patbr < a < x^j + Patbr; y^j - Patbr < b < y^j + Patbr\}, \tag{12}$$

where $Patbr$ is a policy parameter which regulates the extent of the area, accounting for the breadth of the patent system. The length of patent rights is determined by the $Patlen$ parameter which in our baseline scenario is set to 20 time steps, in line with the observed duration of patents. A newly discovered product is patented only if it does not infringe an existing patent. If, instead, it falls into a "forbidden" area, the innovating firm is not allowed to start its production and it is forced to stick to its old product.[13] Once a patent is granted, the patenting firm keeps its exclusion rights until the patent expires. While products whose patent has expired cannot be patented again, we allow for the possibility of "me-too" patenting in their neighboring area (DiMasi and Faden, 2011).

[13] In this version of the model we avoid introducing litigation costs. Insofar as they imply a net welfare loss, our results will provide a conservative assessment (downward-biased) of the impact of patents.

2.4 Pricing and market dynamics

Firms set the prices for their products according to markup rules. In each submarket, the price charged is given by:

$$p^j_{i,t} = (1 + m^j_{i,t})uc, \tag{13}$$

where uc are unit production costs (supposed to be exogenous for simplicity) and m is a submarket- and firm-specific markup.[14] This implies that firms face identical and invariant unit costs as we do not model process innovation.

When a firm enters in a new submarket, the initial markup is drawn from a uniform distribution defined over $[m^{min}, \hat{m}]$, which also might reflect firms' earlier fixed R&D costs. Markups are updated at any time step according to the dynamics of market power. More specifically, we assume a discontinuous adjustment in the form:

$$m^j_{i,t} = \begin{cases} min\{m^j_{i,t-1} + v^j_{i,t};\ m^{max}\}, & \text{for } g(sales)^j_{i,t-1} \geq \tau \\ m^j_{i,t-1}, & \text{for } \rho < g(sales)^j_{i,t-1} < \tau \\ max\{m^j_{i,t-1} - v^j_{i,t-1};\ m^{min}\}, & \text{for } g(sales)^j_{i,t-1} \leq \rho, \end{cases} \tag{14}$$

where: $\tau > 0$; $\rho < \tau$ and $m^{max} > m^{min} > 0$. The parameters m^{max} and m^{min} impose respectively upper and lower bounds on markups. In particular, the parameter m^{max} might also be influenced by price regulation by public authorities, wherever price controls are adopted (notably not in the USA). The term $g(sales)$ stands for the growth rates of sales experienced by the firm in submarket j, while τ and ρ represent thresholds above (or below) which the firm will adjust its markup and v is the (stochastic) adjustment from a uniform distribution with support $[v^{min}, v^{max}]$. Intuitively, markup adjustments occur as a response to sufficiently large variations in market shares, as proxied by past sales growth.[15]

Total demand in each submarket (D^j) evolves according to a logistic function of time (starting from the time of first discovery of the submarket):[16]

$$D^j = \frac{D^{max}}{1 + e^{-\gamma_D(t - t^j_0)}}, \tag{15}$$

with $D^{max}, \gamma_D > 0$. The term t^j_0 stands for the time when the submarket was first discovered,

[14] As a simplifying assumption, we normalize uc to 1.

[15] Our markup adjustment rule intends to catch the intuition that firms enjoying market power tend to increase prices, "as much as the buyer can take" (Orsenigo et al., 2006). Since we do not observe in the data the parameters in Equation 14, we calibrate them in order to match median firm profitability observed in the EU R&D Investment Scoreboard Top 100 pharmaceutical companies, 2016-2019.

[16] As the pharmaceutical sector is characterized by demand elasticities across therapeutic areas close to zero (Orsenigo et al., 2006), separating demand across submarkets is a relatively mild assumption.

D^{max} is the maximum level of demand and γ_D accounts for the speed of saturation.[17]

Total demand is allocated to individual firms via a process of market selection. More specifically, we use a quasi-replicator dynamics to determine firms market shares (f) according to their competitiveness (or fitness, fit), defined as:[18]

$$fit^j_{i,t} = z(x^j_{i,t} + y^j_{i,t}) + (1 - z)1/p^j_{i,t}. \tag{16}$$

Thus, in each submarket j, product fitness is measured as a weighted average of overall quality and the inverse of price, where $z \in [0, 1]$ defines their relative weights.[19] Then, market shares are computed as:

$$f^j_{i,t} = f^j_{i,t-1}(1 + \mu \frac{fit^j_{i,t} - \bar{fit}^j_t}{\bar{fit}^j_t}), \tag{17}$$

with $\mu > 0$. The variable $\bar{fit}$ represents the weighted average fitness in submarket j while the parameter μ accounts for the strength of competition and market selection.[20] In economic terms, the quasi-replicator equation implies that firms that are more efficient than the average (i.e. those producing high-quality drugs and charging low prices) will expand relatively to their competitors in the same submarket. When a firm discovers a new submarket its initial market share is set to one, while, as a firm enters in an existing submarket, it starts with a near-zero market share (f^{min}).

Firms total sales are then computed aggregating sales from each product:

$$sales_{i,t} = \sum_{j \in P_{i,t}} f^j_{i,t} D^j_t, \tag{18}$$

where P is the set of submarkets where firm i operates at time t. Accordingly, total net profits are computed subtracting R&D costs (RD) and production costs ($Q_{i,t}uc$) from total sales:

$$\Pi_{i,t} = sales_{i,t} - RD_{i,t} - Q_{i,t}uc, \tag{19}$$

[17] For simplicity, we assume that D^{max} and γ_D are uniform across submarkets, that is, demand dynamics is identical in different therapeutic fields. In future versions of the model we plan to allow for heterogeneous demand trajectories and study possible interactions with patent regimes.

[18] For an in-depth presentation of replicator dynamics of this type see Dosi et al. (1995) and Dosi et al. (2016).

[19] It is widely recognized that price competition has a limited role in the Pharmaceutical industry while product innovation remains the dominant driver of market success (Orsenigo et al., 2006). For this reason, we set the parameter z to 0.8 in our baseline parametrization, attributing larger relevance to product quality vis-à-vis prices.

[20] Specifically, the variable $\bar{fit}$ is computed as: $\bar{fit}^j_t = \sum_{i \in I_{j,t}} fit^j_{i,t} f^j_{i,t-1}$, where $I_{j,t}$ is the set of firms competing in submarket j at time t.

where $Q_{i,t}$ stands for production volumes by firm i at time t.[21]

2.5 Entry and Exit

At the end of each time step, firms abandon less profitable submarkets. Specifically, we assume that they leave a submarket when their market share is below a minimum threshold (f^{min}). When a firm exits from all the submarkets it is considered dead and replaced by an entrant, thus keeping fixed the total number of firms. Entrants first randomly draw a submarket and then pick their initial location in the product landscape by adding a discrete uniform shock (with support: $[\lambda, \omega]$) to the weighted averages of incumbents' x and y.[22]

The patent system also feeds back to the process of entry and exit. If the product introduced by entrant falls into the area protected by a patent (cf. Eq. 12), the firm cannot start production and is forced to leave the market, i.e. it is replaced by another entrant in the next step.

3 Results

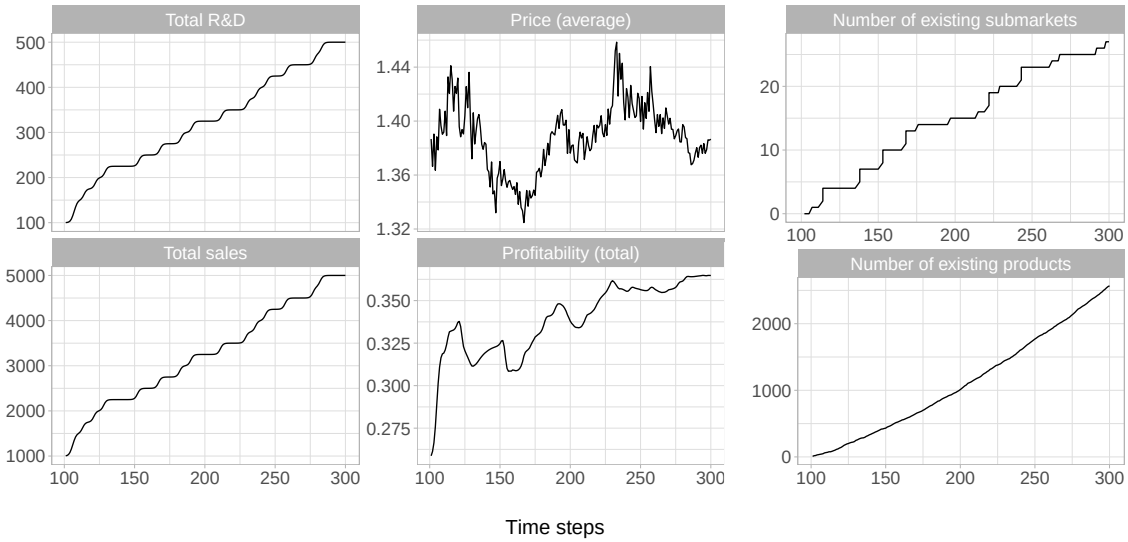
As typical with evolutionary agent-based models, there are no closed-form analytical solutions, and the results are analyzed by means of Monte Carlo simulations (50 runs), in order to average out the effects of different realizations of random shocks (Fagiolo et al., 2019). We initialize the model with 100 identical firms randomly located in a single submarket. We simulate the model for 300 time steps and always discard the first 100 observations to potentially remove the transient phase of the model.

Model parameters are calibrated, whenever possible, using empirical data. In particular, as already mentioned in Section 2, the R&D investment share parameter, s^{RD}, is set equal to 10%, in line with top 100 pharmaceutical companies median R&D intensity in the EU Industrial R&D Investment Scoreboard (years 2016-2019). Furthermore, patent length ($Patlen$) is set equal to 20 periods from filing date, in line with European and US patent law (we assume that each time step correspond to a year). As reliable data on markups are lacking, we impose values for parameters in the markup adjustment rule (m^{max}, m^{min}, τ, ρ) in order to obtain a median profitability of 14% consistent with that observed for top 100 pharmaceutical companies in the EU Industrial R&D Investment Scoreboard. Moreover, data from the Business Enterprise Research and Development Survey run by US National Science Foundation show that pharmaceutical firms devote a much lower share of their

[21] Production volumes are simply computed as: $Q_{i,t} = \sum_{j \in P_{i,t}} \frac{sales^j_{i,t}}{p^j_{i,t}}$.

[22] The initial market share of the entrant is f^{min} and the initial markup charged on its product is draw from an uniform distribution with support $[m^{min}, \hat{m}]$.

Figure 1: Baseline run: time series of main industry-level variables



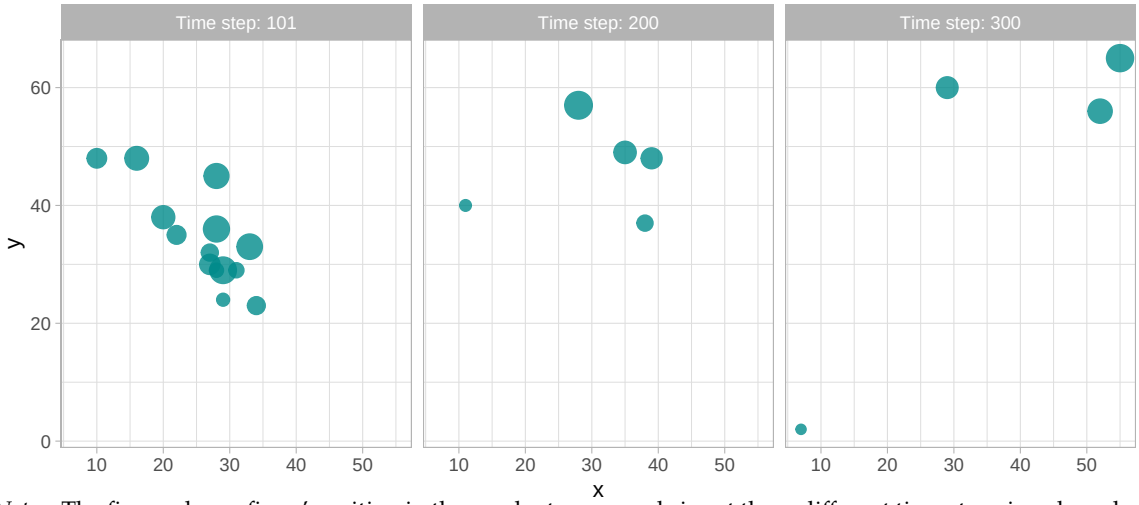
total R&D to basic research, as compared to applied research and development. Although we cannot directly calibrate these shares due to the lack of an explicit modeling of the development phase in our framework, we tried to embed this information by simply assuming a relatively lower share of innovation activities allocated to the investigation of undiscovered therapeutic areas (s^C). Finally, a higher relative weight, $z = 0.8$, is given to quality, with respect to price, in the definition of firms' fitness. This is in line with evidence suggesting a low demand elasticity with respect to price changes in the pharmaceutical sector (Orsenigo et al., 2006). The baseline parametrization is reported in Table A.1.

In the next sections, we assess how the model fares in a typical simulation, considering the emergent results for a baseline run (see Section, 3.1). We then empirically validate the model (cf. Section 3.2), i.e. we investigate its ability to reproduce empirical regularities. Finally, we perform an ensemble of policy experiments regarding the patent system (see Section 3.3).

3.1 Emergent results for a baseline run

Let us start by presenting results for a baseline run of the model. Figure 1 shows the dynamics of some industry-level variables. Consistently with the historical evidence (Bottazzi et al., 2001; Scherer, 2010; Malerba and Orsenigo, 2015), the model generates growth in total sales and R&D spending as a result of new demand opportunities arising from the discovery of new submarkets. The total variety of products available to consumers also increases over time as the industry grows. Moreover, profitability and prices display medium-run fluctuations reflecting shakeouts in the market driven by the emergence of

Figure 2: Baseline run: firms' position and size in a single submarket



Notes: The figure shows firms' position in the product space and size at three different time steps in submarket 1. Bigger dots represent firms characterized by larger size.

submarkets, as well as by the entry of new firms in product areas previously protected by patents.

The regular patterns at the industry-level mask the continuous processes of learning and selection at the microeconomic level, wherein firms try to develop new drugs in order to increase their product portfolios and gain market share in different markets. Such an ongoing process of differentiation leads to the emergence of a core group of leader firms. Within a single submarket, as depicted in Figure 2, firms spread over time along the product space and move sequentially to products with higher quality as a result of their innovation activities. Figure 3, instead, shows the dynamics of market shares in each submarket and for the industry as a whole. Firms that move to new submarkets enjoy a first-mover advantage and become leaders in the new therapeutic areas, until, eventually, the entry of competitors overturns their leadership.

Finally, we report some evidence on how patents affect innovation and technological diffusion in Figure 4, which describes the evolution of the areas protected by patents in a single submarket as well as the products whose patent has expired. As firms introduce and patent new drugs, some areas (in red) of the product space will become inaccessible to other firms. The dimension of the protected areas is entirely dependent on the breadth of the patent system which, therefore, shapes both the rate and direction of product innovation. Nevertheless, as patents expire (green points in the space), the underlying products can be easily imitated, thus, favouring innovation diffusion.

Figure 3: Baseline run: dynamics of market shares in each submarket and in the global industry

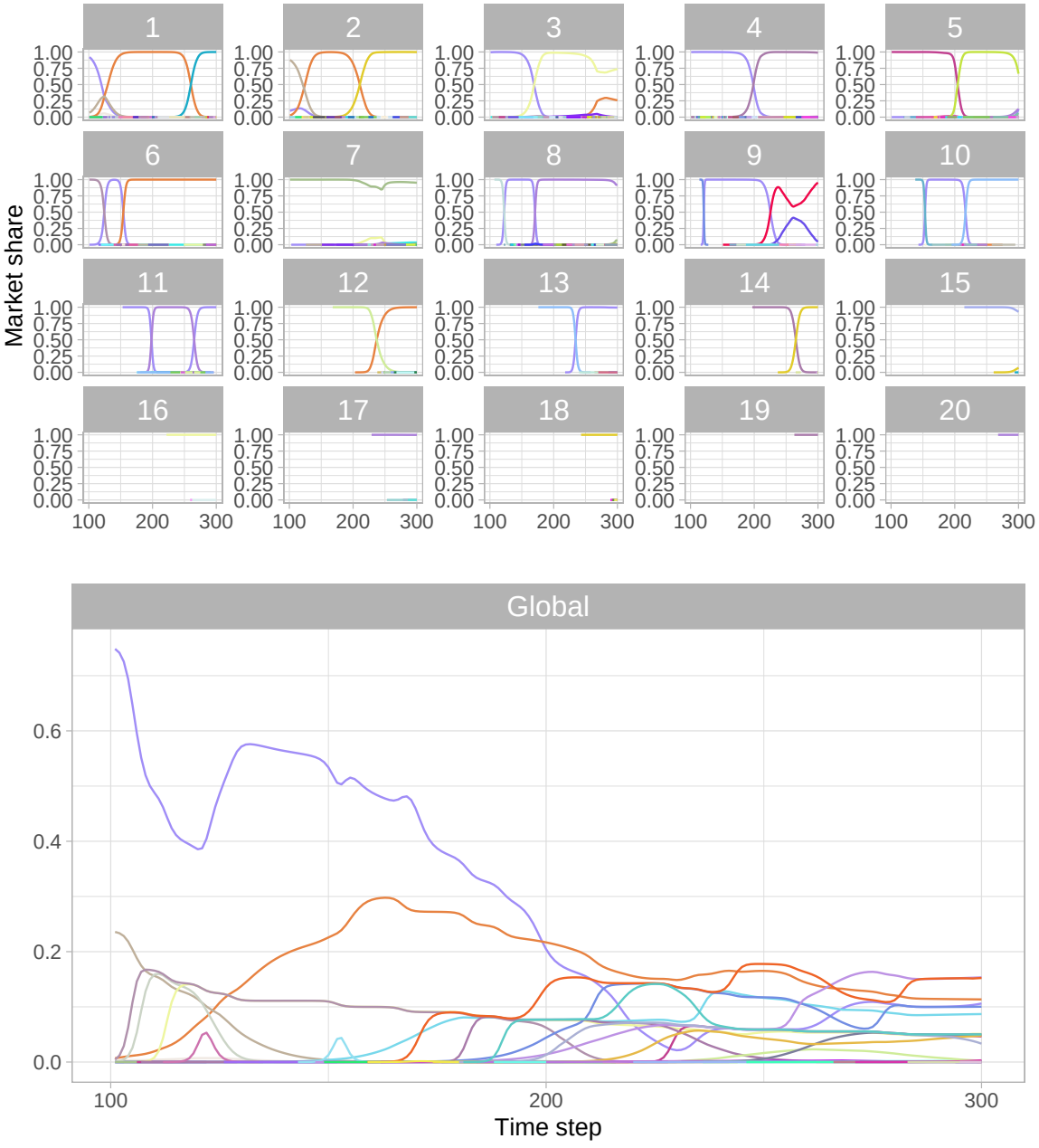
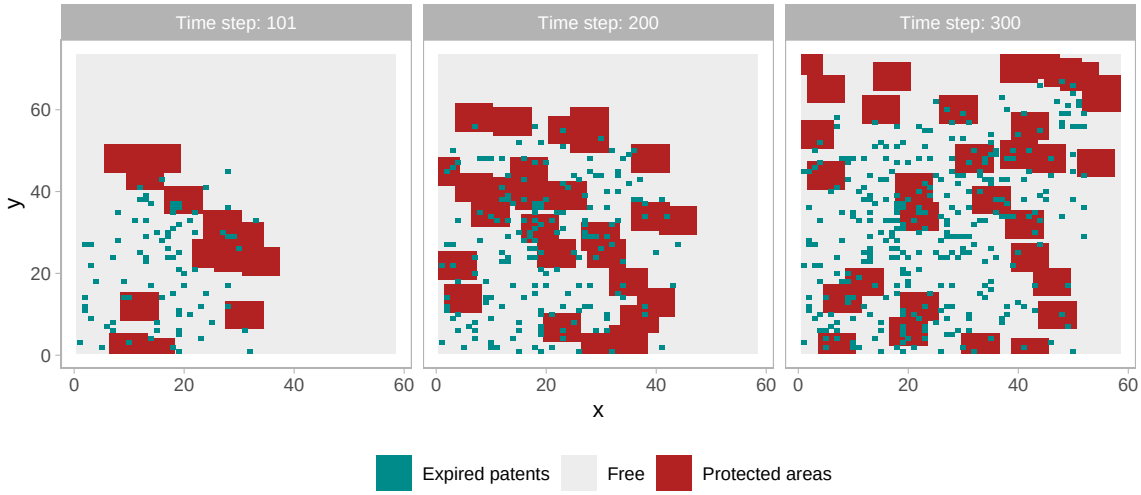


Figure 4: Baseline run: patterns of patent protection in a single submarket



Notes: The figure shows the evolution at three different time steps in submarket 1 of the areas protected by the patent system (in red), as well as of the products with expired patents (in green). Areas in grey represent free and discovered points of the product space.

3.2 Empirical regularities of the pharmaceutical industry

Let us now explore in more detail the performance of the model in reproducing the empirical regularities that characterize the pharmaceutical industry (as documented in Bottazzi et al., 2001; Bottazzi and Secchi, 2005; Scherer, 2010; Malerba and Orsenigo, 2015). This is akin to validating the model, following a well-established procedure in the ABM literature (Windrum et al., 2007).[23] The snapshot of the results provided by Table 1 shows that the model appears to be successful in replicating a relatively large set of stylized facts.

Table 2 reports Monte Carlo averages for a group of industry-wide variables. As already mentioned, the size of the industry sales and R&D spending, as well as the total number of products grow endogenously over time as a result of firms innovation activities (Scherer, 2010; Malerba and Orsenigo, 2015). At the same time, consistently with the historical evidence (Malerba and Orsenigo, 2015), the model generates the emergence of a relatively stable "oligopolistic core" of large firms (cf. Figure 3 for a baseline run, and Table 2 for the MC average market concentration).

Heterogeneity is an emergent outcome of the model as firms differ in terms of the quality and number of their products, as well as the prices they charge (Malerba and Orsenigo, 2015; Coad, 2019). In turn, this ultimately drives also large differences in size, profits and innovativeness, as visible in Figure 5 for a typical run.

We also check whether our model replicates the real-world distributional properties of firm size and growth rates. Figure 6 shows that the rank-size plot for the distribution of

[23]For recent works in the fields of validation and calibration of ABMs see e.g. Lamperti (2018) and Guerini and Moneta (2017). A survey of the literature is provided by Fagiolo et al. (2019).

Table 1: Summary of stylized facts replicated by the model

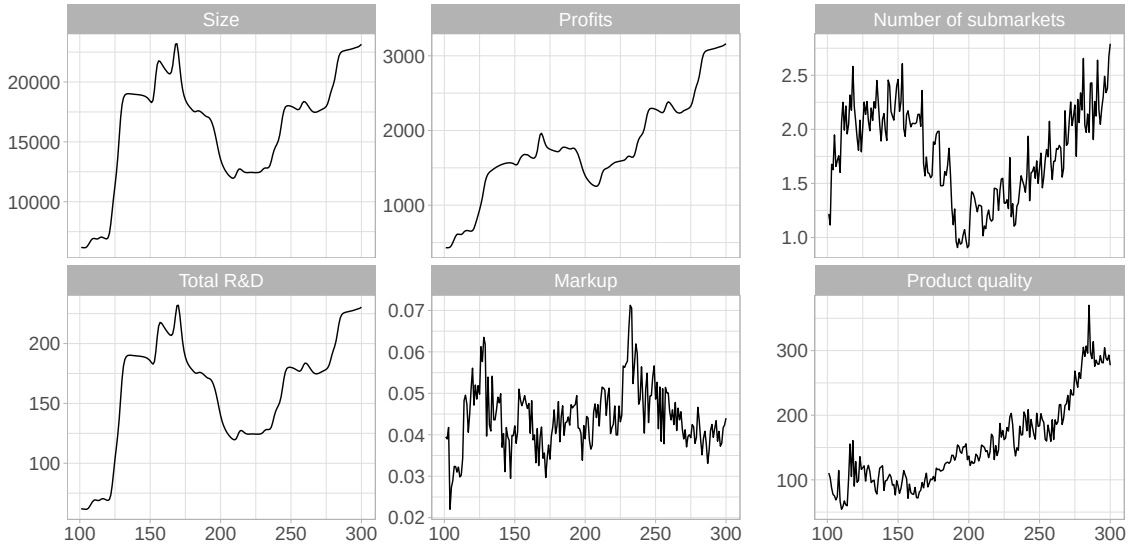
	Stylized fact	Related literature
SF 1	Increasing industry size, R&D and product variety	Scherer (2010); Malerba and Orsenigo (2015)
SF 2	Emergent firm heterogeneity	Scherer (2010); Malerba and Orsenigo (2015)
SF 3	Emergence of an "ologipolistic core" of leaders	Scherer (2010); Malerba and Orsenigo (2015)
SF 4	Right-skewed distributions of firm size	Bottazzi et al. (2001); Bottazzi and Secchi (2005)
SF 5	Fat-tailed distributions of firm growth rates	Bottazzi et al. (2001); Bottazzi and Secchi (2005)
SF 6	Serial correlation in firm growth rates	Bottazzi et al. (2001); Bottazzi and Secchi (2005)
SF 7	Positive relation between firm size and diversification	Bottazzi et al. (2001); Bottazzi and Secchi (2005)

Table 2: Monte Carlo summary statistics for the baseline scenario: industry-level variables.

Number of submarkets	Share of within-submarket innovations blocked	Share of jumps across submarkets blocked	Number of non-blocked products
22.4	0.44	0.32	1700
(1.45)	(0.0068)	(0.0039)	(98.79)
Mark-up (average)	**Profitability (median)**	**Market concentration (average HHI)**	**Yearly industry sales growth**
0.29	0.14	0.24	0.01
(0.0088)	(0.0029)	(0.0283)	(0.0003)

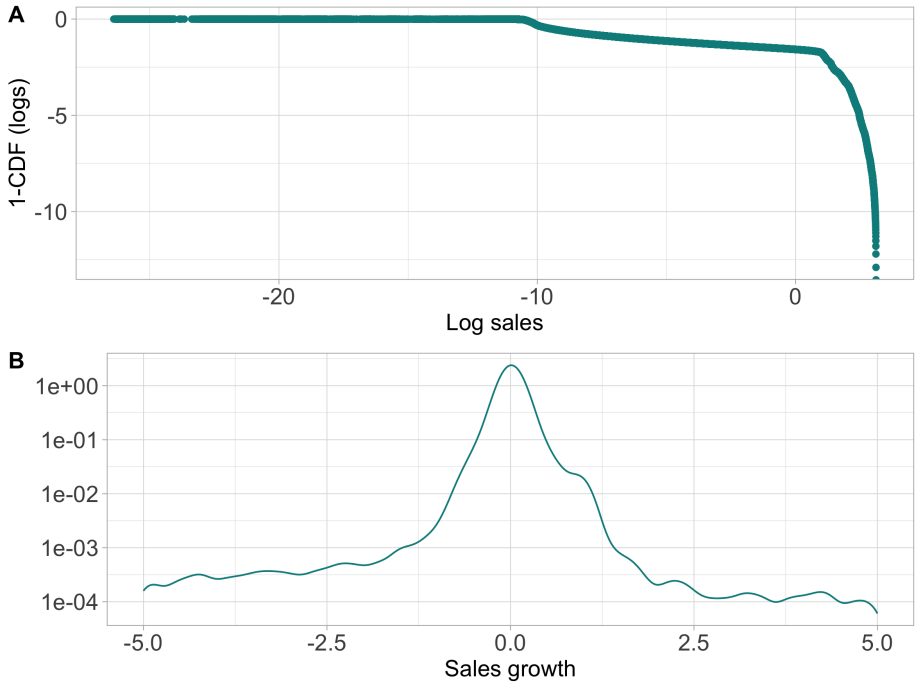
Notes: The Table reports Monte Carlo averages and standard errors (in brackets) of industry-level variables for our baseline scenario. Variables are respectively: (i) the number of submarkets discovered; (ii) the share of innovations (type A) blocked; (iii) the share of innovations (type B) blocked; (iv) the total number of products (non-blocked) discovered; (v) the average markup, weighted by market shares; (vi) median profitability; (vii) tmarket concentration (average Herfindal index); (viii) the yearly average growth of industry sales.

Figure 5: Baseline run: heterogeneity over time



Notes: The figure shows the evolution over time of emergent heterogeneity among firms, captured by the variance within each time step, for different indicators.

Figure 6: Size and growth rates distributions



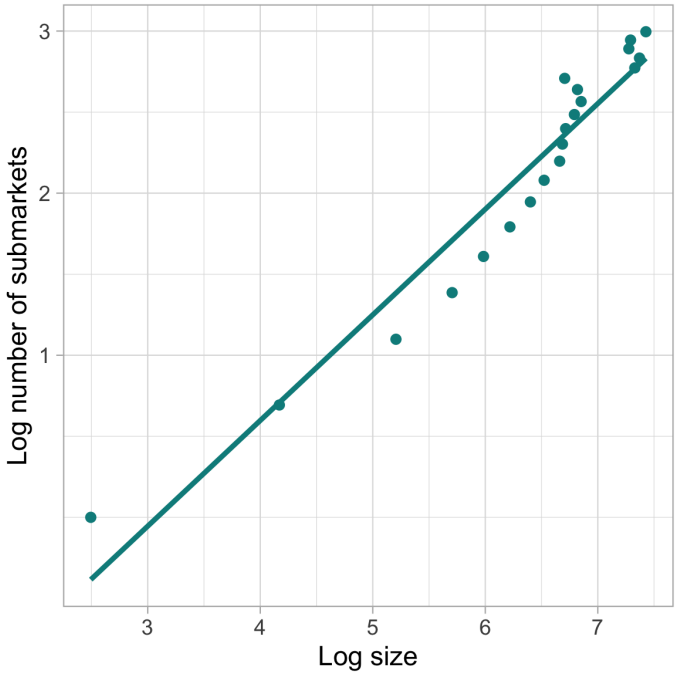
Notes: The figure shows simulated distributions of firm size (panel A) and growth rates (panel B) obtained pooling mean-normalized data from 50 Monte Carlo runs.

Table 3: Growth rates autocorrelation estimates

AR(1)	AR(2)	AR(3)
0.336*	0.214*	0.078
(p=0.067)	(p=0.054)	(p=0.134)
	0.399**	0.378**
	(p=0.014)	(p=0.014)
		0.274**
		(p=0.013)

Notes: The table reports average Monte Carlo coefficients and p-values from the estimation of AR models for firm sales growth rates. Specifically, we estimate the pooled OLS model consistently with Bottazzi and Secchi (2005): $g_{i,t} = \sum_{l=1}^{L} \phi_l g_{i,t-l} + \epsilon_{i,t}$. We allow for up to three lags ($L = 3$).
*p<0.1; **p<0.05; ***p<0.01

Figure 7: Firm size and diversification



Notes: The figure plots in a log-log scale the average firm size versus the number of active submarkets (i.e. those where firms operate).

firm size reveals a right skewed shape where few large firms coexist with several smaller businesses, consistently with previous findings in the empirical literature (Bottazzi et al., 2001; Bottazzi and Secchi, 2005; Dosi, 2007).[24] The distribution of firms growth rates displays the typical Laplacian shape, widely observed in empirical data, suggesting that firm growth is a relatively lumpy process driven by rare large events. At the same time, in tune with the empirical evidence (Bottazzi et al., 2001; Bottazzi and Secchi, 2005; Dosi, 2007), growth rates appear to be serially correlated (cf. Table 3) suggesting the presence of self-reinforcing patterns in growth dynamics.

Finally, we investigate the patterns of diversification in relation to firm size. Various empirical studies documented a positive and log-linear relation between firm size and the number of submarkets where the firm operates (Bottazzi et al., 2001; Bottazzi and Secchi, 2005). Our model is able to replicate this evidence, as highlighted in Figure 7, which plots the average log of firm size versus the log number of active submarkets. Indeed, large firms are more likely to diversify in new therapeutic areas compared to smaller competitors, according to a sort of branching process whereby the existing knowledge bases lead the

[24] In investigating the size distribution we use the following normalization to remove time trends from the data (Bottazzi et al., 2001): $s_{i,t} = \frac{sales_{i,t}}{\frac{1}{N}\sum_{i=1}^{N} sales_{i,t}}$. Accordingly, firm growth rates are computed as: $g_{i,t} = \log s_{i,t} - \log s_{i,t-1}$.

discovery of contiguous fields of application.

Taken together, the validation results show that our model is able to match a broad set of stylized facts both generic and specific to the pharmaceutical industry, thus providing an empirically validated setting which allows us to use the model as a "laboratory for policy experiments" on the role of patents in the pharmaceutical industry. This is the object of analysis in the next section.

3.3 Patents, innovation and market competition

The central policy question of our work is how the patent system affects innovation and competition in the pharmaceutical industry. We tackle this issue by running a set of policy experiments variating over our baseline scenario. We shock at $t = 100$ the two main parameters that regulate the appropriability conditions guaranteed by the patent system: $Patbr$ and $Patlen$. The former affects the extent of patent protection in each submarket's product space, while the latter influences its duration.

Figure 8 shows the effects of changing the breadth of the patent system on different industry outcomes using boxplots of Monte Carlo distributions. To further investigate statistical significance, Monte Carlo averages and the associated standard errors are also reported in Table B.1.

First, increasing the extent of patents reduces exploitable technological opportunities and has a negative impact on innovation within submarkets (innovation type A) and on firm diversification (innovation type B), as measured by the share of blocked products out of the total of products introduced. Intuitively, the broader is the area protected, the higher will be the probability to incur in IPR violations and have your product blocked by the patent system. In a similar fashion, increasing breadth also grants stronger protection to incumbents (especially to market leaders) and entails less innovation from entrants (i.e. a higher share of blocked products for entrants). Interestingly, we find that the reduction in technological opportunities associated to a larger extent of patents also (mildly) hampers the discovery of new submarkets (innovation type C), thus, posing obstacles to the emergence of new drugs for therapeutic needs that are yet unsatisfied. As in our setting total R&D efforts are correlated with sales, they also decrease following the decline in industry size (as compared with the baseline scenario). Overall, the fall in innovation rates translates into less product variety and lower average product quality. Second-order effects of rising patent breadth are higher industry concentration, as well as markups and prices, ultimately driving adverse distributional effects for society.[25]

[25] Although we do not explicitly model income distribution, this finding is linked to a stream of literature which has investigated the impacts of IPR on inequality. In fact, a strengthening of the IPR system is found to lead to more inequality (Adams, 2008). Moreover, Lazonick and Mazzucato (2013) emphasize how such system

Let us now investigate the role of patent length by progressively increasing the corresponding parameter for different values of patent breadth (i.e. $Patbr = 4$ and $Patbr = 10$), in order to explore potential heterogeneous effects. Results are shown in Figure 9 (cf. Table B.2 for the associated Monte Carlo averages and standard errors). We find that increasing the duration of patent rights also negatively affects innovation opportunities, as it decreases the total number of submarkets and products actually explored and developed, and it also results in higher market concentration and prices. In absolute levels, these effects are more dramatic when longer duration is coupled with a higher patent breadth ($Patbr = 10$).

This first ensemble of experiments shows that stronger patents have a negative impact on innovation rates and new drug discoveries, while increasing prices and market concentration. However, such negative results do not take into account potential positive feedback on R&D intensity and information disclosure that may be associated to tighter IPRs. According to the narrative which finds a straightforward formalization in common incentive-based, implicitly rational technological expectation, models, patents ought to provide incentives to firms for increasing their R&D share, while disclosing more information and allowing innovation diffusion (see among a whole tradition Fudenberg et al., 1983; Acemoglu and Akcigit, 2012; Aghion et al., 2019). In the next sections, we study these hypotheses with new simulation exercises.

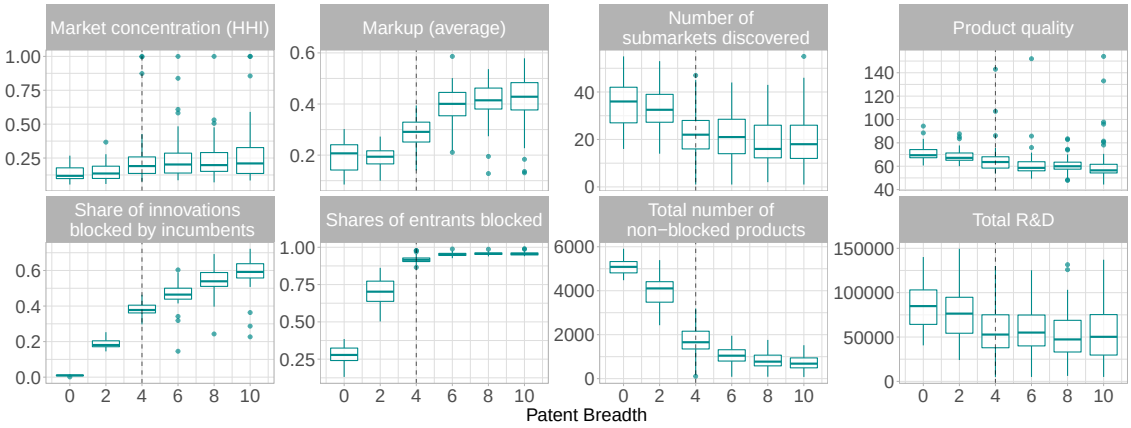
3.3.1 Patents and R&D incentives

In our model, R&D decisions are entirely routinized, that is, firms always invest a fixed shares of their past sales in research. In this setting, stronger IPRs can affect R&D spending of a successfully innovating firm via larger market demand. Nevertheless, as shown by the previous simulations, a stronger patent system may also stifle the imitation and innovation rates of laggard competitors, and if this effect prevails, this results in less innovation and higher prices. Yet, one of the standard arguments used to support the adoption of the patent system is that it can foster higher R&D intensity (c.f. rising R&D per sales). According to this view, firms increase the share devoted to research activities in response to the appropriability incentives provided by patents (Nordhaus, 1969).

Let us then investigate this possibility by jointly varying the breadth of patent ($PatBr$) and the R&D share (s^{RD}). Reliable empirical evidence about the elasticity of R&D investments with respect to patents is not available and less so with the disaggregation of the type of R&D (Budish et al., 2016).

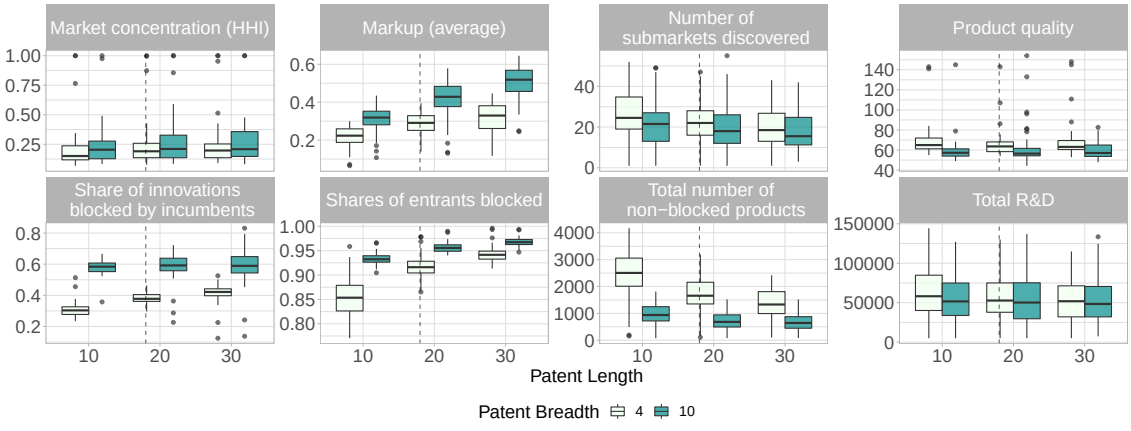
does not entail any balance between risks and rewards from innovation basically leading to the prevalence of value extraction. In that case, innovation-led growth might actually lead to increasing inequality. Relatedly, Stiglitz (2016) has pointed out that the well-known macroeconomic evidence of increasing wealth-income ratios is not due to an increase in productive capital but, instead, to a rise in rents and returns on intellectual property. We leave to future work further investigations in this direction in the context of our model.

Figure 8: Policy experiments: changing patent breadth



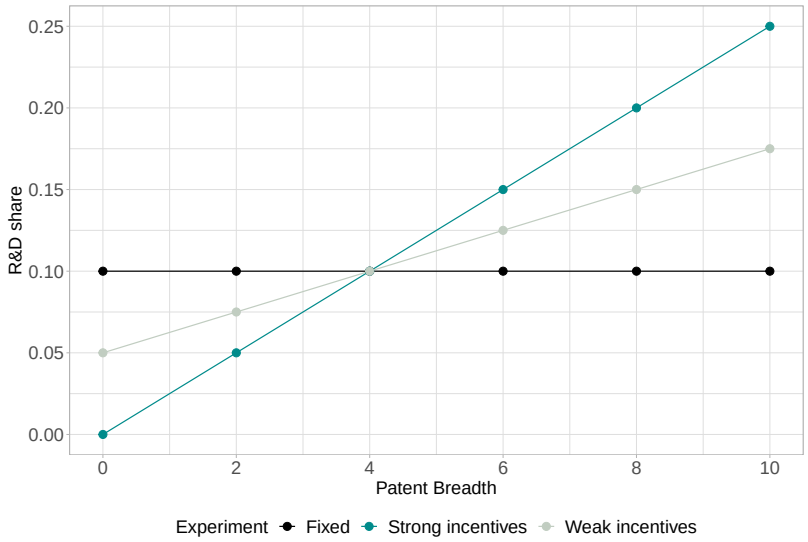
Notes: Monte Carlo distributions for different values of patent breadth, across selected variables. The dashed line represents the baseline scenario. The variables considered are respectively: (i) average Herfindal Index; (ii) average markup, weighted by market shares; (iii) the number of submarkets discovered; (iv) an indicator of product quality at the frontier, measured as: $\frac{1}{J}\sum_{j=1}^{J} X_T^j + Y_T^j$; (v) share of products blocked for incumbents; (vi) share of products from entrants blocked; (vii) total number of products (non-blocked) discovered; (viii) the total R&D spending during the simulation.

Figure 9: Policy experiments: changing patent length



Notes: Monte Carlo distributions for different values of patent length and two levels of patent breadth (i.e. 4 and 10), across selected variables. The dashed line represents the baseline scenario. The variables considered are those reported in Figure 8.

Figure 10: Parameter values for policy experiments under different R&D incentive regimes

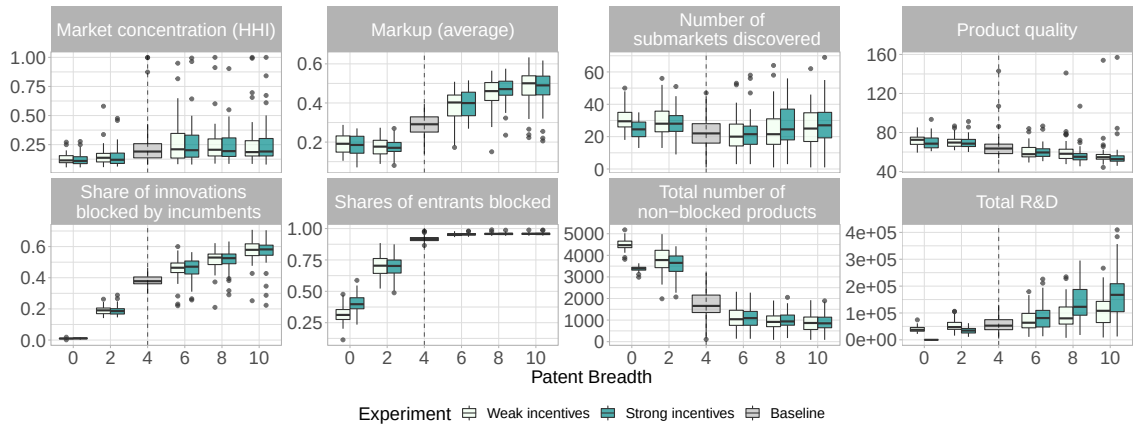


Here we design a scenario that is consistent with some preliminary estimates reported by Budish et al. (2015), who find quite weak R&D incentives associated to an increase in the strength of patent protection, with an elasticity between 7% and 24%. Indeed, we want to experiment with this modeling assumption in detail. First, we let the R&D share (s^{RD}) increase together with $PatBr$ in order to get a percentage increase in R&D in the foregoing range. We label this experiment "weak R&D incentives". Moreover, we explore a scenario, basically in line with conventional theory of incentive-driven search, which we call "strong R&D incentives" scenario. A visual representation of both experiments is reported in Figure 10 which shows the combination the $PatBr$ and s^{RD} used in each setting (for the sake of comparison, also the baseline case with fixed R&D share is shown).

In Figure 11, we analyze these experiments in terms of different innovation and competition outcomes, while Table B.3 shows the Monte Carlo averages across scenarios. Indeed, unlike the foregoing no-incentive opportunity-only driven scenario, total R&D now increases with $Patbr$. And, not surprisingly, the surge is much more pronounced in the "strong R&D incentives" scenario, as firms start from a near-zero share and rise fast their R&D investment when patent protection is granted. The story in terms of innovative outcomes is quite different. Still, under weak "R&D incentives" scenario there is a negative relation between the strength of patents and innovation. Increasing $PatBr$ results in less submarkets, lower number of available products as well as in quality losses. Intuitively, the rise in R&D spurred by the patent system is overcompensated by the associated reduction in exploitable technological opportunities.

When perceived R&D incentives are strong, we find positive effects associated to increasing patent protection only when moving from $Patbr = 0$ to $Patbr = 2$. Within this

Figure 11: Policy experiments under different R&D incentives



Notes: Monte Carlo distributions for different values of patent breadth and two scenarios regarding R&D incentives (weak vs. strong). The dashed line represents the baseline scenario. See Figure 10 for parameter values corresponding to the different scenarios. The variables considered are those reported in Figure 8.

range, the number of (non-blocked) products and submarkets discovered increases while, after reaching the threshold ($PatBr = 2$), we find again detrimental effects on innovation outcomes. Basically, even under the most extreme (and empirically far-fetched) scenario, the balance between domains of exploitable opportunities of innovation, and the incentive to do so, might be profitable for individual firms, but appears to be collectively detrimental in terms of innovation rates.

Also, the adverse consequences of rising patent breadth on competition and consumer welfare persist in all the scenarios considered.

3.3.2 Disclosure effects

Another channel through which the patent system may foster scientific and technological progress is via disclosure effects. When filing patent applications, inventors are obliged to disclose technical information about their innovations (see e.g. Hall et al., 2014, for a review of the literature on the trade-off between secrecy and disclosure). The empirical evidence on these effects provides generally mixed results.[26] In the pharmaceutical sector,

[26]Text-based works have shown that the information disclosed in patent document is often vague and difficult to read (especially for patents filed by private firms, see e.g. Kong et al., 2020). Analyses based on survey of researchers generally find that information disclosure from patents is only marginally relevant for the innovation process (Cohen et al., 2000; Jaffe et al., 2000; Ouellette, 2012). Recent evidence from quasi-experimental studies is also hardly conclusive. For instance, Furman et al. (2018) finds positive effects on local patenting associated to the opening of USPTO regional patent libraries. Gross (2019) focuses on the patent secrecy programs implemented during World War II and documents that protected patents are characterized by reduced follow-on inventions and restricted commercialization (yet, admittedly by the authors, it is not possible to fully attribute the long-term effects to secrecy). Baruffaldi and Simeth (2020) study the introduction of the American Inventors Protection Act and show that earlier disclosure facilitate knowledge flows but only within existing geographical and technological boundaries. Finally, de Rassenfosse et al. (2020) analyze the Invention Secrecy Act documenting a negative relation between the enforcement of secrecy orders on patents

the effectiveness of disclosure ought to allow easier technology transfers among firms and universities, as well as a more "ordered" path of search avoiding the costly duplication of efforts (Coriat and Orsenigo, 2014). In our model, information disclosure effects are captured by parameters γ_1 and Ψ (in Eq. 10 and 11) which respectively facilitate the imitation of existing products and the entry in new submarkets after the expiration of patents. We investigate the role of information disclosure under four scenarios, namely low disclosure ($\gamma_1 = 0.5, \Psi = 0.5$); baseline ($\gamma_1 = 1, \Psi = 1$); high disclosure ($\gamma_1 = 2, \Psi = 2$); and a limiting case with "very high disclosure" ($\gamma_1 = 50, \Psi = 50$).

The simulation results are reported in Figure 12 (Monte Carlo averages and standard errors for each experiments are in Table B.4). Substantial effects emerge only in the limit case ("very high disclosure") wherein we observe a reduction in the share of blocked products introduced by incumbents as well as a moderate decrease in average product quality. Quite intuitively, more disclosure shapes the direction of the innovative process towards imitating products with expired patents (i.e. the development of generic drugs), rather than towards quality enhancements. On the one hand, the patterns of search become relatively more "efficient" since firms are discouraged from developing "me too" drugs (i.e. these located in proximity of existing ones) while they are incentivized to copy products only after the expiration of patents. This, in turn, might lead to lower litigation rates and less blocked products. On the other hand, disclosure favours imitation as compared to quality-enhancing innovations within submarkets, thus, resulting in a mild decrease in the average product quality. Nevertheless, neither the number of submarkets discovered nor total product variety appear to be substantially affected by disclosure parameters.

Finally, we also run simulations combining together the “strong R&D incentives” and the “very high disclosure” settings in order to build a scenario even more favourable to patents. We did not find any significant difference with the results of the two experiments taken alone.[27]

4 Conclusions

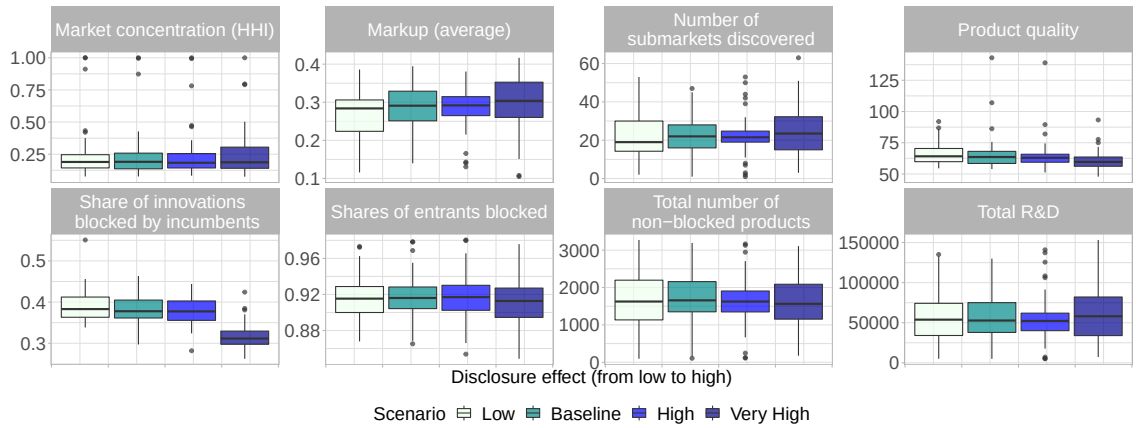
In this work, we have studied how different configurations of the patent system affect innovation and competition in pharmaceuticals, indeed, one of the industries where IPR seem to matter most (Cohen et al., 2000; Levin et al., 1987).

To address such research question, we have developed an evolutionary, agent-based model tailored on the pharmaceutical industry. Firms in the model compete and innovate in different therapeutic areas according to routinized search rules, while a process of market

and follow-on inventions.

[27]Simulation results for this experiment are available from the authors upon request.

Figure 12: Varying patent disclosure effects



Notes: Monte Carlo distributions for different values of the parameters that are related to disclosure effects of the patent system (γ_1 and Ψ respectively). The parameter values considered are: low ($\gamma_1 = 0.5$, $\Psi = 0.5$); baseline ($\gamma_1 = 1$, $\Psi = 1$); high ($\gamma_1 = 2$, $\Psi = 2$); very high ($\gamma_1 = 50$, $\Psi = 50$). The variables considered are those reported in Figure 8.

selection determines their demand, market shares and profitability. The patent system has a dual role: on the one hand, it protects innovations by preventing firms to move into areas of the product landscape nearby the newly discovered drugs, while, it might favour information disclosure and easier imitation after the expiration of patent rights.

In a baseline scenario, the model yields results in line with observational data and replicates a set of robustly established stylized facts of the pharmaceutical industry, including a few micro distributional properties and an increasing industry size and concentration (cf. Section 3.2). We then run policy experiments studying different degrees of tightness of IPR systems in terms of patent breadth and length. Our results suggest that larger extent and duration of patent rights have negative consequences not only on competition, but also on innovation outcomes. In addition to rising prices and market concentration, a stronger patent regime entails lower product variety and quality, as well as, interestingly, less breakthrough discoveries. We also implemented different policy scenarios varying the strength of positive R&D incentives provided by patents and the effectiveness of information disclosure. Patents exert positive effects on innovation only when combining a very large (arguably unrealistic) response of R&D investment under a low patent breadth. Introducing stronger information disclosure effects only alter the direction of the innovative process, fostering imitation and the development of generic drugs.

Our work can be extended in different ways. First, we mean to explicitly model the role of public funding of basic research and the spillovers to private firms. Second, it is important to model at greater detail the different phases which lead to drug discovery and commercialization. Third, as already mentioned, we intend to explore the evolutionary implications of ecologies of firms characterized by different propensities to innovate and

imitate. Finally, one can study which policy tools and, more generally, innovation system (e.g., innovation prizes, public drug discovery, etc.) can boost innovation and the discovery of new therapeutic areas at the lower cost for the public (see e.g. the policy proposals in Cimoli et al., 2014).

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Appendix A Benchmark parametrization

Table A.1: Parameters

Description	**Symbol**	**Value**
Montecarlo replications	MC	50
Number of time steps	T	300
Number of firms	N	100
R&D investment share	s^{RD}	0.1
Allocation shares to innovation activities	(s^A, s^B, s^C)	(0.5, 0.3, 0.2)
Upper bound probabilities for innovation activities	$(pmax^A, pmax^B, pmax^C)$	(0.4, 0.4, 0.02)
Quality of innovation system parameters	$(\theta^A, \theta^B, \theta^C)$	(0.1, 0.1, 0.05)
Minimum search area for firms at the frontier	$\hat{k}$	1
Speed in exhaustion of innovation opportunities	γ_k	0.1
Sensitivity to distance (within-submarket)	γ_0	0.2
Strength of patent disclosure effect (within-submarket)	γ_1	1
Strength of patent disclosure effect (across submarkets)	Ψ	1
Patent breadth	$Patbr$	4
Patent length	$Patlen$	20
Maximum markup	m^{max}	0.9
Minimum markup	m^{min}	0.05
Maximum markup when entering an existing submarket (type B)	$\hat{m}$	0.2
Upper threshold for markup adjustment rule	τ	0.08
Lower threshold for markup adjustment rule	ρ	-0.02
Maximum submarket demand	D^{max}	250
Initial dimension of submarkets	$(Xinit, Yinit)$	(20, 20)
Speed of demand saturation	γ_D	1
Relative weight for quality (vs. price) in fitness definition	z	0.8
Strength of competition and market selection	μ	1
Market share threshold for exit	f^{min}	0.00001
Lower bound for entry shock	λ	-5
Upper bound for entry shock	ω	2

Appendix B Tables of results

Table B.1: Experiments varying Patent Breadth ($Patbr$)

	$Patbr = 0$	$Patbr = 2$	$Patbr = 4$	$Patbr = 6$	$Patbr = 8$	$Patbr = 10$
Total R&D	84510.15	76413.48	58239.43	56725.35	53340.56	53808.25
	(3740.987)	(4098.998)	(4091.742)	(3933.733)	(4145.594)	(4407.809)
Total number of products	5092.52	4034.16	1699.98	1042.92	813.14	710.90
	(47.135)	(88.328)	(98.778)	(61.767)	(52.219)	(48.436)
Number of submarkets discovered	35.54	32.78	22.42	21.16	19.20	19.30
	(1.382)	(1.340)	(1.451)	(1.398)	(1.404)	(1.563)
Share of innovations blocked by incumbents	0.010	0.186	0.380	0.466	0.538	0.590
	(0.000)	(0.003)	(0.005)	(0.010)	(0.010)	(0.013)
Share of entrants blocked	0.278	0.700	0.918	0.953	0.957	0.957
	(0.008)	(0.012)	(0.003)	(0.002)	(0.001)	(0.001)
Product quality	70.938	68.891	66.317	61.991	60.891	62.943
	(0.903)	(0.844)	(1.997)	(2.064)	(1.033)	(2.805)
Market Concentration (HHI)	0.134	0.151	0.237	0.254	0.254	0.273
	(0.007)	(0.009)	(0.028)	(0.026)	(0.023)	(0.029)
Markup (average)	0.197	0.191	0.285	0.392	0.407	0.413
	(0.008)	(0.006)	(0.009)	(0.011)	(0.011)	(0.014)

Notes: The table reports Monte-Carlo averages for each experiment and the associated standard errors (in brackets). In each experiment we use a different value of patent breadth ($Patbr$). The baseline is $Patbr = 4$. The outcome variables considered are those reported in Figure 8.

Table B.2: Experiments varying Patent Length ($Patlen$) for different values of Patent Breadth ($Patbr = 4$ and $Patbr = 10$)

	$Pabr = 4$			$Pabr = 10$		
	$Patlen = 10$	$Patlen = 20$	$Patlen = 30$	$Patlen = 10$	$Patlen = 20$	$Patlen = 30$
Total R&D	63203.91	58239.43	53329.40	57183.15	53808.25	53272.11
	(4645.082)	(4091.742)	(4106.602)	(4370.521)	(4407.809)	(4212.679)
Total number of products	2457.36	1699.98	1321.08	981.62	710.90	652.40
	(126.760)	(98.778)	(82.889)	(60.601)	(48.436)	(44.254)
Number of submarkets discovered	26.26	22.42	19.42	22.12	19.30	18.60
	(1.724)	(1.451)	(1.481)	(1.635)	(1.563)	(1.460)
Share of innovations blocked by incumbents	0.312	0.380	0.413	0.581	0.590	0.586
	(0.007)	(0.005)	(0.009)	(0.007)	(0.013)	(0.016)
Share of entrants blocked	0.854	0.918	0.942	0.933	0.957	0.968
	(0.006)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Product quality	68.925	66.317	68.826	59.387	62.943	60.180
	(2.340)	(1.997)	(2.622)	(1.909)	(2.805)	(1.202)
Market Concentration (HHI)	0.216	0.237	0.255	0.244	0.273	0.265
	(0.028)	(0.028)	(0.030)	(0.026)	(0.029)	(0.027)
Markup (average)	0.217	0.285	0.319	0.308	0.413	0.505
	(0.008)	(0.009)	(0.012)	(0.010)	(0.014)	(0.012)

Notes: The table reports Monte-Carlo averages for each experiment and the associated standard errors (in brackets). In each experiment we use different combinations of patent breadth ($Patbr$) and length ($Patlen$). The baseline is $Patlen = 20$ and $Patbr = 4$. The outcome variables considered are those reported in Figure 8.

Table B.3: Experiments varying Patent Breadth and R&D shares under different incentives regimes (weak vs. strong incentives)

	$Patbr = 0$		$Patbr = 2$		$Patbr = 4$	$Patbr = 6$		$Patbr = 8$		$Patbr = 10$	
	Strong $s^{RD} = 0.000001$	Weak $s^{RD} = 0.05$	Strong $s^{RD} = 0.05$	Weak $s^{RD} = 0.075$	Baseline $s^{RD} = 0.1$	Weak $s^{RD} = 0.125$	Strong $s^{RD} = 0.15$	Weak $s^{RD} = 0.15$	Strong $s^{RD} = 0.20$	Weak $s^{RD} = 0.175$	Strong $s^{RD} = 0.25$
Total R&D	0.67	39009.29	35066.42	53486.47	58239.43	71745.48	87603.62	92132.52	135655.64	108959.03	167879.30
	(0.028)	(12700.164)	(1820.320)	(3189.684)	(4091.742)	(5683.268)	(6909.077)	(7117.381)	(10061.620)	(1631.635)	(7908.228)
Total number of products	3383.42	4497.78	3579.76	3809.82	1699.98	1074.70	1116.00	927.02	1001.54	856.36	888.64
	(16.466)	(37.761)	(79.309)	(91.699)	(98.778)	(71.042)	(72.573)	(56.742)	(59.720)	(54.673)	(58.270)
Number of submarkets discovered	24.44	30.26	28.38	29.88	22.42	22.26	22.56	23.32	27.00	25.04	27.52
	(0.789)	(1.077)	(1.114)	(1.527)	(1.451)	(1.681)	(1.681)	(1.866)	(1.922)	(1.745)	(1.981)
Share of innovations blocked by incumbents	0.011	0.010	0.189	0.191	0.380	0.455	0.461	0.516	0.513	0.578	0.565
	(0.001)	(0.000)	(0.004)	(0.004)	(0.005)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.012)
Share of entrants blocked	0.402	0.312	0.697	0.701	0.918	0.953	0.954	0.958	0.958	0.959	0.958
	(0.010)	(0.010)	(0.013)	(0.012)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Product quality	69.906	72.248	69.746	70.326	66.317	60.123	60.391	60.917	56.834	57.073	56.360
	(0.955)	(0.819)	(0.834)	(0.824)	(1.997)	(1.037)	(0.970)	(1.968)	(1.284)	(2.103)	(2.264)
Market Concentration (HHI)	0.121	0.126	0.148	0.154	0.237	0.262	0.262	0.248	0.237	0.259	0.258
	(0.007)	(0.007)	(0.012)	(0.012)	(0.028)	(0.026)	(0.027)	(0.025)	(0.021)	(0.028)	(0.026)
Markup (average)	0.186	0.194	0.175	0.179	0.285	0.381	0.396	0.446	0.467	0.481	0.475
	(0.007)	(0.007)	(0.006)	(0.007)	(0.009)	(0.012)	(0.009)	(0.011)	(0.010)	(0.013)	(0.013)

Notes: The table reports Monte-Carlo averages for each experiment and the associated standard errors (in brackets). In each experiment we use different combinations of patent breadth ($Patbr$) and the share of R&D spending (s^{RD}). These combinations correspond to the incentive regimes depicted in Fig. 10, i.e. "weak" vs. "strong" R&D incentives. The outcome variables considered are those reported in Figure 8.

Table B.4: Experiments varying disclosure parameters

	Low disclosure	**Baseline**	**High disclosure**	**Very High disclosure**
Total R&D	58123.93	58239.43	56273.02	60376.44
	(4699.322)	(4091.742)	(4219.197)	(4777.782)
Total number of products	1675.76	1699.98	1634.12	1630.82
	(107.377)	(98.778)	(95.411)	(96.657)
Number of submarkets discovered	21.88	22.42	22.02	24.64
	(1.733)	(1.451)	(1.479)	(1.830)
Share of innovations blocked by incumbents	0.390	0.380	0.379	0.317
	(0.006)	(0.005)	(0.005)	(0.004)
Share of entrants blocked	0.916	0.918	0.917	0.912
	(0.003)	(0.003)	(0.004)	(0.004)
Product quality	66.075	66.317	65.132	61.052
	(1.153)	(1.997)	(1.785)	(1.083)
Market Concentration (HHI)	0.243	0.237	0.242	0.254
	(0.029)	(0.028)	(0.028)	(0.027)
Markup (average)	0.272	0.285	0.283	0.296
	(0.008)	(0.009)	(0.008)	(0.010)

Notes: The table reports Monte-Carlo averages for each experiment and the associated standard errors (in brackets). In each experiment we use different combinations of information disclosure parameters (γ_1, Ψ). We explore the following scenarios: low ($\gamma_1 = 0.5$, $\Psi = 0.5$); baseline ($\gamma_1 = 1$, $\Psi = 1$); high ($\gamma_1 = 2$, $\Psi = 2$); very high ($\gamma_1 = 50$, $\Psi = 50$). The outcome variables considered are those reported in Figure 8.