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R&D Behaviour and the Emergence of Fat-Tailed Firm Size Distributions*

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Abstract

This paper presents a simple boundedly rational model of a firm and consumer behaviour. We formulate an entry game, where every firm decides on investing in R&D for inventing a new product that will appeal to certain group of consumers. The success depends on the amount of funds available for the project as well as firm's familiarity with the relevant proportion of taste space. We identify the section of parameter space where firms have an incentive to diversify. For these parameter constellations the model results in rich industrial dynamics. Equilibrium firm size distributions are heavy tailed and skewed to the right. The heaviness of the tail depends on one industry-level parameter.

Key Words: R&D · Product innovation · Market knowledge · Firm size distribution
JEL codes: C72 · D21 · L11

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1 Introduction

Research and development is an essential activity of a modern successful firm. Planning of this process is a complex problem as firms have to take into account many aspects, including dynamic external factors, like competition. R&D behaviour of firms has been an important topic in economics for last three decades and there are important theoretical (Harris and Vickers, 1985), as well as empirical (Cohen and Klepper, 1992) contributions to its understanding. Successful R&D requires possession of special skills and knowledge by firms. It has also been suggested that there are certain increasing returns to doing R&D (Nelson, 1982).

Research and development is the main contributor to firm growth. Therefore, we should look at R&D behavior when we try to explain the shape of firm size and growth rate distributions. However, to the best of our knowledge, this has not been done in the literature. Early models of firm growth, like Gibrat (1931), Kalecki (1945) and Simon (1955), were concerned with the firm size distributions but ignored deliberate efforts in R&D activities (de Wit, 2005). More recent models, like Nelson (1982), Cohen and Klepper (1992) and Klette and Kortum (2004), that explicitly model firm R&D decisions, do not analyze resulting firm size distributions.

This paper presents a model of firm R&D behaviour and studies firms' R&D incentives and resulting firm size distributions. The central notion in our model is that of a taste space. We assume that each product can be located at a point in a taste space. Its location in this space fully characterizes a product. Products that are located closer in taste space are better substitutes to each other, thus we can assume they are traded on a common market, we call this market a submarket. The definition of a submarket is, in principle, the outcome of the taste space discretization: each discrete unit is a separate submarket. Consequently, all the products traded on the same submarket are located at the same point in taste space.

In this environment we formulate an entry game where constant number of firms decide on target submarkets for their potential products in order to grab the higher share of constant stream of aggregate profits. In order to come up with the suitable product, firm has to invest in product development. R&D is a stochastic process and its success rate depends on amount of money invested as well as knowledge of the target submarket by the firm. Innovating on new markets results in acquisition of new knowledge by the firm, which increases productivity of its R&D. However, while deciding on target market, firms fall short of perfect rationality: they do not take into account the effects of prospective new knowledge on their future R&D performance. This assumption is in line with empirical findings that suggest that expertise and knowledge that firms posses is often acquired in unplanned ways (Andrews, 1971; Porter, 1980; Nelson and Winter, 1982), in our case by innovating on new (sub)markets.

Proximity in taste space has two implications. One is that the shorter the distance, the better substitutes a pair of products are to each other. The other is that closely located submarkets will be somewhat similar, thus we can safely assume that knowledge of one of the submarkets can be used (with somewhat lower productivity) to innovate on nearby submarkets. These intuitions describe two important parameters that we use for the analysis: the submarket specificity of producer knowledge and the submarket specificity of consumer tastes.[1]

Starting from a homogenous cohort of entrants firm size heterogeneity arrises naturally in our model. It turns out that the equilibrium firm size distribution is fat tailed, which is consistent with empirical findings (Cabral and Mata, 2003; Coad, 2009). We further analyze the dependance of the tail index of this distribution on the parameters of the model. We show that for the relevant fraction of parameter space, tail index depends only on submarket specificity of firm knowledge.

The remainder of the paper is organized as follows. Section 2 presents a model of firm R&D behaviour and growth. Section 3 presents the results concerning R&D incentives and equilibrium firm size distributions. The last section concludes.

2 The model

The model has a distinctive structure from most R&D models: the economy does not consist of intermediate and final good sectors. There is only one sector, thus one global market, on which substitute goods are traded. Each product on the market has only one property: the location in the taste space. We assume that although all the products existing in the economy are substitutes, degree of substitutability between any pair of products varies. More precisely, we assume that that the taste space is a uni-dimentional periodic lattice (a circle). Then higher (circular) distance between any pair of locations will be reflected in lower degree of substitutability between products located at those locations.

Each product is produced by one and only one producer. This is due to the existence of property rights. However, each firm can hold many patents and produce many goods. We assume that there is no market for intellectual property. We have two reasons for assuming that firms are not willing to sell their intellectual property. Firstly, imperfections on information market drives the offer price downwards (Arrow, 1962). Secondly, because innovations are more valuable to the innovator than to other firms (Cohen and Levinthal, 1989), which makes the offer price to seem even lower.

As there is no transfer of property rights, the only way to grow is through R&D process.To model research and development, it is important to have an idea about the distribution of R&D intensities in a typical industry. This topic has attracted interest in economic literature

[1] There are the discrete counterparts of location specificity of knowledge and preferences in taste space.

(Cohen, Levin, and Mowery, 1987). Empirical work on various industries suggests that the cross-sectional correlation coefficient between firm's R&D expenditures and sales is nearly 0.8 (Cohen and Klepper, 1992). It also has been found that firm size has virtually no effect on R&D intensity (Cohen, Levin, and Mowery, 1987). This points to the fact, that R&D intensity is relatively constant across the firms. It has been reported that R&D intensity is not the result of maximizing behaviour of firms, but is rather based on rules of thumb and that its adjustment is quite sluggish (Silverberg and Verspagen, 1994). This suggests that R&D intensity is relatively constant across time too.

Therefore, we assume that R&D intensity is constant. Thus, we do not allow producers to choose the amount of money they want to spend on research. Rather we restrict their choice to the decision of whether they want to do R&D or not. If they decide to do so, they allocate a constant share of their current profits to this activity. They can also decide on the target location for their prospective product. More precisely, they first decide on where in taste space they want to place the product and then perform the R&D aimed at coming up with the product that would be suitable to be placed at target location.

Productivity of an R&D project depends on the amount of money invested in it (thus, on the current profits of the firm), as well as on the market knowledge (of the target location) of the producer. Recall that the lower distance between a pair of locations in taste space implies high substitutability between products placed at those locations. Then it seems intuitive to assume that familiarity with a certain location in a taste space might help to innovate in nearby locations. We assume that producers have good market knowledge of locations where they currently have products. We also assume that the productivity of their knowledge decreases with the shortest distance between the location on which a given producer operates and the target location.

Demand combines two well-known frameworks. The first is the well known ideal variety model by Lancaster (1979). In this framework a consumer has a preferred variety of a product on the market (her ideal variety). It also has preferences for other varieties. Then, taking into account prices and strength of preferences for each of the products consumer decides which product to buy. The other framework is constant elasticity of substitution utility function, which is a workhorse of modern neoclassical economics. In this framework elasticity of substitution between any pair of products is constant. To combine these two frameworks we make share coefficients of CES utility function proportional to the strength of preference of each consumer for the given location in taste space.

Consider consumers having heterogeneous tastes. Following Lancaster (1979) we assume that for each consumer there is a unique location in taste space which corresponds to her ideal variety. Her preferences decay with the distance from this location, reaching the lowest value on the opposite side of the circle representing taste space. Then, utility maximization implies that the demand of a consumer for a product depends on her preference for the location of this product in taste space, as well as on available alternatives and prices.

We analyze the industry of a fixed size. The consequence is that every time a new product enters the market it has a business stealing effect on incumbents, as now total demand has to be redistributed on more products. This is Schumpeterian creative destruction effect. However, this effect is not homogenous across products in our model. As the new product is a better substitute for products located in close proximity in taste space, it steals more business from them, relative to those at greater distances.

Given the description of the model we can analyze R&D incentives of firms. Due to the positive contribution of market knowledge to R&D productivity, firms have incentive to innovate in close proximity to their products, as they have good knowledge of that portion of taste space. However, due to asymmetric creative destruction this might not be optimal as investing close to your old products might result in duplicating efforts in attracting consumers. This indirectly increases the cost of innovation. Therefore, at any point in time, given the market situation there will be an optimal point in taste space where a firm would want to innovate (provided that it wants to innovate).

2.1 General setup

So far we have thought about taste space to be continuous, however it is in many ways convenient to discretize it. In this case location of every product will be not a point, but rather one dimensional unit on a taste circle. Then we can construct a new unit of analysis.

Definition 1. We define a submarket as the collection of products that are located on the same discrete unit in taste space.

Consider the finite number of submarkets located on a unidimensional periodic lattice. Location on this lattice will be referred to as $i \in \{1, 2, \ldots, I\}$. Finite number of consumers are indexed by $s \in \{1, 2, \ldots, S\}$. There are also a finite number of firms indexed by $n \in \{1, 2, \ldots, N\}$ producing finite number of products. These products are indexed by $m \in \{1, 2, \ldots, M_t\}$ at any time.

Each firm produces as many products as many patents is holds. All the technologies used in the economy are neutral to scale. Profits of firm n at time t are given by

$$\pi_t^n = \sum_{j \in \mathscr{P}_t^n} (p_{j,t} - w_{j,t}) D_{j,t}, \tag{1}$$

where $p_{j;t}$, $w_{j;t}$ and $D_{j;t}$ are price, unit cost and total demand of product j at period t respectively and $\mathscr{P}_t^n$ is the set of products firm n produces.

We assume that producers are price takers and that prices are set somehow outside the market. We consider the case when all the products in the economy have the same price and it is constant over time $p_{i,t} = p_{j,t} = p_{i,\tau} = p$, $\forall i, j, t, \tau$. Moreover, we assume that production costs are homogenous across products and time (no process innovation). As a result, our firms' profits are a constant share of their total demand $p_{j,t} - w_{j,t} = \gamma$, $\forall n, j, t$. This reduces producer's profit function to $\pi_t^n = \gamma \sum_{j \in \mathscr{P}_t^n} D_{j,t}$ and collapses producer's problem into the maximization of its total demand.

In this environment we can define an entry game. Producers engage in product innovation. If firm n decides to do R&D at time period t, it can choose an appropriate submarket and invest a constant share of its last period's profits into this activity $R_t^n = \beta \pi_{t-1}^n$.[2] Firms decide on the location of the prospective product in a taste space. Or, equivalently, on the target submarket. Given the amount of money allocated to R&D (R) and market knowledge of the producer for target submarket i, innovation success probability is given by $r_{i,R} \in [0, 1]$.

Recall that the success rate of R&D process depends on the knowledge base that a firm has. We have assumed that firms have good knowledge of taste space close to the locations of their current products. Then successful innovation outside submarkets where firms currently operate results in new knowledge that can be used by firms in order to increase their R&D productivity on a certain potion of the taste space. Thus, firms can behave strategically in entering new markets for acquisition of knowledge. However, according to the discussion in introduction to the paper we know that knowledge base of firms is acquired in unplanned ways. Therefore, we exclude these incentives for strategic behavior from our analysis. We analyze producers that are not fully rational. Rather they are myopic in this respect. In this case the game boils down to a constant number of producers stochastically placing new products on chosen submarkets in order to maximize their contemporaneous profits.

In order to analyze producer incentives recall that there is creative destruction in our model. Once a new product is placed on the market the incumbents' shares decrease. Therefore, while planning their actions, perfectly rational (and able) firms should take into account the effect of creative destruction that might come from other firms innovating. However, we assume that global information structure is such that producers do not observe each others incentives.[3] Hence, producers can not take into account this effect in a rigorous way. What they can do

[2]Although empirical findings point to the fact that firms spend constant share of their revenues on R&D, our assumption of scale neutrality implies that constant share of revenues is constant share of profits.

[3]This might be, for example, due to the fact on a global anonymous market it is impossible to identify who produces which product.

instead is to "anticipate" (estimate) the size of this effect on their markets and set their market attitudes accordingly. In this case we will have pessimistic firms, who anticipate destruction of large share of their markets (due to other producers innovating) and optimistic firms who anticipate the size of this effect to be small. Formation and updating of market attitudes are out of scope of this paper. Instead, we model optimistic firms who estimate the destruction of their market share due to innovation of other firms to be negligible.[4]

Let $\psi \in \{0; 1\}$ describe the decision of a producer to conduct R&D at a given time period or not. Then the problem of myopic, optimistic, risk-neutral producers can be written as

$$\max_{\psi,i} \gamma \left(\psi r_{i,R} \left(D^i_\iota + \sum_{j \in \mathscr{P}^n_{t-1}} D^i_j \right) + (1 - \psi r_{i,R}) \sum_{j \in \mathscr{P}^n_{t-1}} D_j \right) - \psi R, \tag{2}$$

where D_j describes the total demand for product j at current situation (if the producer does not innovate) and D^i_j describes the demand if the producer places a new product on the market i. ι is the index of a new product.

Taking into account the definition of R, we can see that value of γ does not affect the optimization problem (as long as $\gamma \neq 0$) and thus we can rewrite utility maximization as

$$\max_{\psi,i} \psi r_{i,R} \left(D^i_\iota + \sum_{j \in \mathscr{P}^n_{t-1}} D^i_j \right) + (1 - \psi(r_{i,R} + \beta)) \sum_{j \in \mathscr{P}^n_{t-1}} D_j. \tag{3}$$

Solution to this problem gives the answer to two questions, to engage in R&D or not, and if yes on which submarket. This fully characterizes the incentives of players of our game. Then, we can define the equilibrium of the game.

Definition 2. Equilibrium of the game is reached when $\psi^{n*}_t = 0$, $\forall n$.

This definition corresponds to the Nash Equilibrium as it implies no player has any further incentives to unilaterally deviate from the current situation (invest in R&D). After this point, industry becomes stagnant and all the variables become time-invariant.

2.2 Functional forms: exponential decay in preferences and knowledge

Demand. Consider consumers having CES utility function of a form

$$U^s_t = \sum_{m=1}^{M_t} {k^s_m}^{\frac{1}{\gamma}} {C^s_{m,t}}^{\frac{\gamma-1}{\gamma}}, \tag{4}$$

[4] Alternatively we could make firms homogenous in this respect and introduce a parameter that would control their beliefs. For example, they would always anticipate that δ% of their market share will get stolen. This enters the profit maximization problem (later equation (2)) in a trivial way and does not modify the incentive structure, but rather only the size of expected profits. Our approach of modeling optimistic firms is equivalent to setting $\delta = 0$.

where $C^s_{m,t}$ is the amount of product m consumed by the consumer s at time t, k^s_m is the parameter that reflects the strength of the preference of consumer s towards the product m.

Maximization of the consumer utility under equal prices implies that

$$\frac{k^s_m}{C^s_{m,t}} = \frac{k^s_j}{C^s_{j,t}}, \tag{5}$$

$\forall m, j \in \{1, 2, \ldots, M_t\}$, which means that consumption of products by each consumer will be proportional to their consumer-specific preference coefficients.

Products traded on the same submarket are placed at the same location in taste space. Therefore, $\forall s\ k^s_m = k^s_j$, if m and j are traded on the same submarket. Then, optimality condition (5) implies that the total demand on the submarket is equally split by all the products on the submarket. This might seem to suggest that producers that are monopolists on their submarkets will never have incentives to invest in placing a new product on the submarket. However, this is not true, as coming up with the new variety of the product will attract consumers from neighbouring submarkets and increase the size of the submarket.

In order to clearly see this implication of the CES utility function consider the following example.

An example: 2×2×2 economy. There are only two producers and only two consumes in the economy. Each firm produces one product. Firm 1 produces product 1, firm 2 produces product 2. Consumer utility maximization implies condition: $k^1_1/C^1_1 = k^1_2/C^1_2$ for consumers 1 and $k^2_1/C^2_1 = k^2_2/C^2_2$ for consumer 2. Then, the consumption of product 1 by the consumer 1 is $C^1_1 = \frac{k^1_1}{k^1_1+k^1_2}\frac{Y^1}{p}$, where Y^1 is the income of consumer 1. Demand of each product by each consumer can be calculated similarly. Profits of two firms in this case will be $\pi_1 = \gamma\left(C^1_1 + C^2_1\right) = \frac{\gamma}{p}\left(\frac{k^1_1}{k^1_1+k^1_2}Y^1 + \frac{k^2_1}{k^2_1+k^2_2}Y^2\right)$ and $\pi_2 = \gamma\left(C^1_2 + C^2_2\right) = \frac{\gamma}{p}\left(\frac{k^1_2}{k^1_1+k^1_2}Y^1 + \frac{k^2_2}{k^2_1+k^2_2}Y^2\right)$.

Consider the situation when firm 1 places a new product (3) on the same submarket where its old product is traded. Then we have $k^1_3 = k^1_1$ and $k^2_3 = k^2_1$. In this case the profits of two firms are $\pi'_1 = \gamma\left(C^1_1 + C^2_1 + C^1_3 + C^2_3\right) = \frac{\gamma}{p}\left(\frac{2k^1_1}{2k^1_1+k^1_2}Y^1 + \frac{2k^2_1}{2k^2_1+k^2_2}Y^2\right)$ and $\pi'_2 = \gamma\left(C^1_2 + C^2_2\right) = \frac{\gamma}{p}\left(\frac{k^1_2}{2k^1_1+k^1_2}Y^1 + \frac{k^2_2}{2k^2_1+k^2_2}Y^2\right)$. It can be easily verified that $\pi'_1 > \pi_1$. Therefore monopolists might have incentives to invest in R&D on own submarket. This, in principle, can be viewed as investment in expanding a submarket.

In order to incorporate the intuition that consumers' preferences decay with the distance from her ideal variety we make share coefficient k dependent on distance in taste space. In particular we assume that this dependence is exponential:

$$k_i^s = \frac{1}{(d_i^s + 1)^c}, \tag{6}$$

where d_i^s is the distance of submarket i from consumer s's favorite submarket and c is the parameter that controls the strength of submarket specificity of consumer tastes. It governs the rate of decay of preferences with distance: the higher c, the more submarket specific consumers' preferences are.

To see that these functional forms (equations (4) and (6)) imply that products located closer in taste space are better substitutes, we can look at the marginal rate of substitution

$$MRS_{jm} = \left(\frac{k_m^s}{k_j^s}\right)^{\frac{1}{\gamma}} \left(\frac{C_m^s}{C_j^s}\right)^{-\frac{1}{\gamma}}. \tag{7}$$

Assume product m is located at consumer s's preferred location in taste space (m is s's ideal variety). Then by substituting equation (6) into equation (7) it can be readily seen that $\partial MRS_{jm}/\partial d_j > 0$, which implies that with increasing distance from her ideal variety consumer needs bigger and bigger amounts of product j as a compensation for a unit of product m in order to stay at the same utility level. This means that with increasing distance product j becomes worse substitute to product m.

Equations (5) and (6) imply that product purchases of a single consumer are proportional to $(d_i^s + 1)^{-c}$. In this discussion, as well as in rest of the paper, we assume that the taste structure is the same for every consumer. In other words, that parameter c is constant across population, it is the characteristics of the society, rather then of an individual.

Now we can calculate the demand for product m (that is traded on submarket i) coming from agent s:

$$D_{m,i}^s = \frac{(d_i^s + 1)^{-c}}{\sum_{j=1}^{M} (d_j^s + 1)^{-c}} \frac{Y^s}{p}. \tag{8}$$

Then, the total demand for the product m at time t would be

$$D_{m,i,t} = \sum_{s=1}^{S} \frac{(d_i^s + 1)^{-c}}{\sum_{j=1}^{M} (d_j^s + 1)^{-c}} \frac{Y^s}{p}. \tag{9}$$

Supply. Producers can engage in R&D activity. For successful R&D they need two types of input: money and knowledge. We assume that the knowledge of the firm about specificities of the submarket declines with the distance from the submarket on which the firm currently operates. Formally:

$$\kappa_i^n = \frac{1}{(d_i^n + 1)^a}, \tag{10}$$

where d_i^n is the *shortest* distance from the submarket where the firm n currently operates to the submarket i. a controls the level of submarket specificity of producer knowledge. We assume a is a characteristics of a population of firms, thus it is constant across them.

The process described above implies that with successful innovation on new (to the firm) markets the firm gains additional knowledge. This is due to the fact that entering new markets guarantees better positioning of the firm for certain portions of the taste space, thus familiarity to new submarkets increases R&D productivity on part of the new submarkets where firm can potentially diversify in later time periods.

We assume, that the probability that firm will come up with the suitable product to be placed on at the submarket i after investing R into the R&D project during one period, is given by

$$r_i^n = \frac{\kappa_i^n}{1 + \exp(q_1 - q_2 R^n)}, \tag{11}$$

where R^n is the sum of money that firm n invested in R&D, q_1 (> 0) and q_2 (> 0) are the parameters controlling the productivity of investment in R&D, which satisfy the constraint $(1 + \exp(q_1))^{-1} \approx 0$.[5] Equation (11) implies that $\partial r/\partial R > 0$, $\partial^2 r/\partial R^2 < 0$, $\partial r/\partial d < 0$, $\partial^2 r/\partial d^2 > 0$ and $r_{i,0} \approx 0 \; \forall i$.

We restrict firms from taking more than one R&D project at a time and assume that if R&D is not successful the invested resources are lost without return and do not contribute to further knowledge accumulation.

3 Analysis

The dynamic game presented in section 2 describes a complex, path-dependent process. Functional forms and the interdependence structure necessary to capture important intuitions make it analytically not tractable. Thus we employ tools of numerical analysis in order to demonstrate the implications of the model. By definition, any complex system is sensitive to initial conditions. We analyze only a subset of initial conditions which is relevant for the research question. As we conduct numerical analysis with large number of parameters we are confronted with the problem of presenting the results. There are two major parameters: c and a. We present the results in the space of these parameters and examine the effects of changes in values of other

[5]This is required in order to ensure that the probability of innovating is zero unless there is some money spent on R&D.

parameters on these results.

3.1 Settings

Initial conditions. The main aim of the paper is to study the effect of the knowledge which is unpurposefully acquired through R&D process. The model endogenously generates the heterogeneity of firms with respect to their knowledge base, R&D incentives and size. As we want to understand only the contribution of the non-intended knowledge acquisition towards the shaping of firm size distribution we need to analyze industries where there is no initial heterogeneity in size and prospects of growth across firms. This requires several things. Firstly, that initial demand and amount of knowledge is the same for every producer. Secondly, that existing products at the onset of industry are uniformly distributed over submarkets. Thirdly, that the aggregate demand is uniformly distributed over submarkets. This limits the set of interesting initial conditions.

There is a simple setup that satisfies all of the requirements listed above: each producer initially has one and only one product, there is one and only one product traded on each submarket, and there is exactly one consumer per each submarket whose preferred variety is traded on this submarket. We use this simple constellation in our numerical exercise. There are several other variants of initial conditions satisfying requirements. All of them produce similar results to the ones presented here.

Parameter values. As mentioned earlier, there are two important parameters in analysis of R&D incentives and firm size distributions. One is c - submarket specificity of consumer tastes, a demand-side parameter, which controls for the level of substitutability between products traded on different submarkets. Higher c implies that consumers' tastes are more submarket specific, which means that products traded on distant submarkets are poorer substitutes to each other. The other parameter is a - submarket specificity of producers' knowledge, a supply side parameter, which controls for how useful the knowledge of a certain submarket is for the R&D process on other submarkets. Higher a implies that knowledge is more submarket-specific.

Contribution of other parameters to a qualitative analysis of R&D incentives and firm size distribution is of second order of importance. Thus, for presenting the results we keep the rest of the parameters constant. The parameter values used in the numerical analysis in following sections are given in table 1. The last four entries reflect the initial conditions of the industry. The selection of parameter values (except for q_1) is more or less arbitrary. However, the effects of their changes are examined. Regarding q_1, it was selected to be high enough in order for the innovation probability in case of no investment in R&D to be sufficiently close to zero even on

parameter	description	value
γ	Profit margin	1
p	Price	1
Y	Per capita income per time period	10
β	R&D intensity	0.15
q_1	R&D productivity parameter (1)	6
q_2	R&D productivity parameter (2)	4
I	Number of submarkets	200
S	Number of consumer	200
N	Number of firms	200
M_0	Initial number of products	200

Table 1: Parameter values for the numerical analysis.

markets where producers already operate.

3.2 Results

3.2.1 R&D incentives at the onset of homogenous industry

As discussed in section 3.1, initial conditions to our model have been selected to ensure the homogeneity of firms (except the location of their initial product). Because of this, initially every firm has the same problem to solve. In this section we analyze the effect of supply and demand parameters (a and c) on incentives of firms whether to do R&D and if yes, where (on which submarket) to do it.

To answer this question we rewrite producers problem taking into account equations (9) and (11) that specify the demand and distribution of firm's R&D productivity over submarkets. It is easy to verify that in case of parameter values given in table 1 initial demand for a product will be equal to $D = Y$, and that $R = \beta Y$. This, together with equations (9) and (11), allows us to represent R&D productivity (r) and demand for a product after innovation at a certain market (D^i) as the functions of only one variable - a distance from producer's initial submarket (d). Hence, we can rewrite D^i as D^d and consequently the equation (3) as

$$\max_{\psi \in \{0,1\}} \begin{cases} \max\limits_{d \in [0; S/2]} r^d (D^d + D^0) + (1 - r^d - \beta) Y & \text{if } \psi = 1 \\ Y & \text{if } \psi = 0. \end{cases} \quad (12)$$

For the sake of the analysis of behaviour implied by equation (12) we can differentiate between three regimes: (R1) $\psi^* = 0 \Rightarrow$ no research and development; (R2) $\psi^* = 1$ and $d^* = 0 \Rightarrow$ R&D on submarket where firm already operates (no diversification); and (R3) $\psi^* = 1$ and $d^* > 0 \Rightarrow$ R&D on unknown submarkets (diversification). These three regimes result in radically different market dynamics. R1 describes stagnant markets, where there are no new products. In this

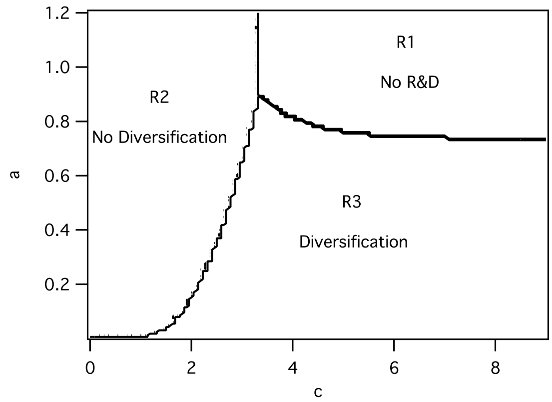

Figure 1: Borders of the three regimes.

case the game starts at equilibrium, thus there is no market share redistribution. In case of R2 everybody has an incentive to do R&D on the markets where they are currently operating. This means that every producer stays as a monopolist on its initial market.[6]

The most interesting case is R3. In this case every producer has an incentive to explore new markets. This results in diversified firms. From the market knowledge point of view, this is the only interesting regime, because in this case new market knowledge is acquired by innovating firms. New knowledge facilitates their R&D process, thus only this regime is characterized by increasing returns to innovation.

Simultaneously modeling heterogenous preferences and product location in taste space makes function D^d complicated even in this simple setup. Due to this it is impossible to solve the producers' profit maximization problem (12) analytically. Therefore we solve it numerically. Figure 1 presents the solution. It plots the borders of three regimes in c-a parameter space, while other parameters are set to the values specified in table 1. As one can see, higher values of both parameters simultaneously result in the least interesting regime R1. Combination of lower values of c with higher values of a results in R2, while higher values of c with lower values of a results in R3.

Intuition for this result is quite simple. High values of a imply that market knowledge is highly submarket specific. This, in turn, implies that R&D productivity on unknown submarkets is very low. As a result, the only option for producers is to innovate on their own markets (or not to innovate at all). On the contrary, low values of a imply productivity on remote submarkets that is only slightly lower compared to the productivity on markets where producers already operate. Thus, investing in remote submarkets becomes an available option.

On the demand side high values of c imply that consumers have very submarket specific tastes. In this situation, new product put on producer's own market will capture a big share

[6]There are some exception to this, which will be discussed later in section 3.2.2.

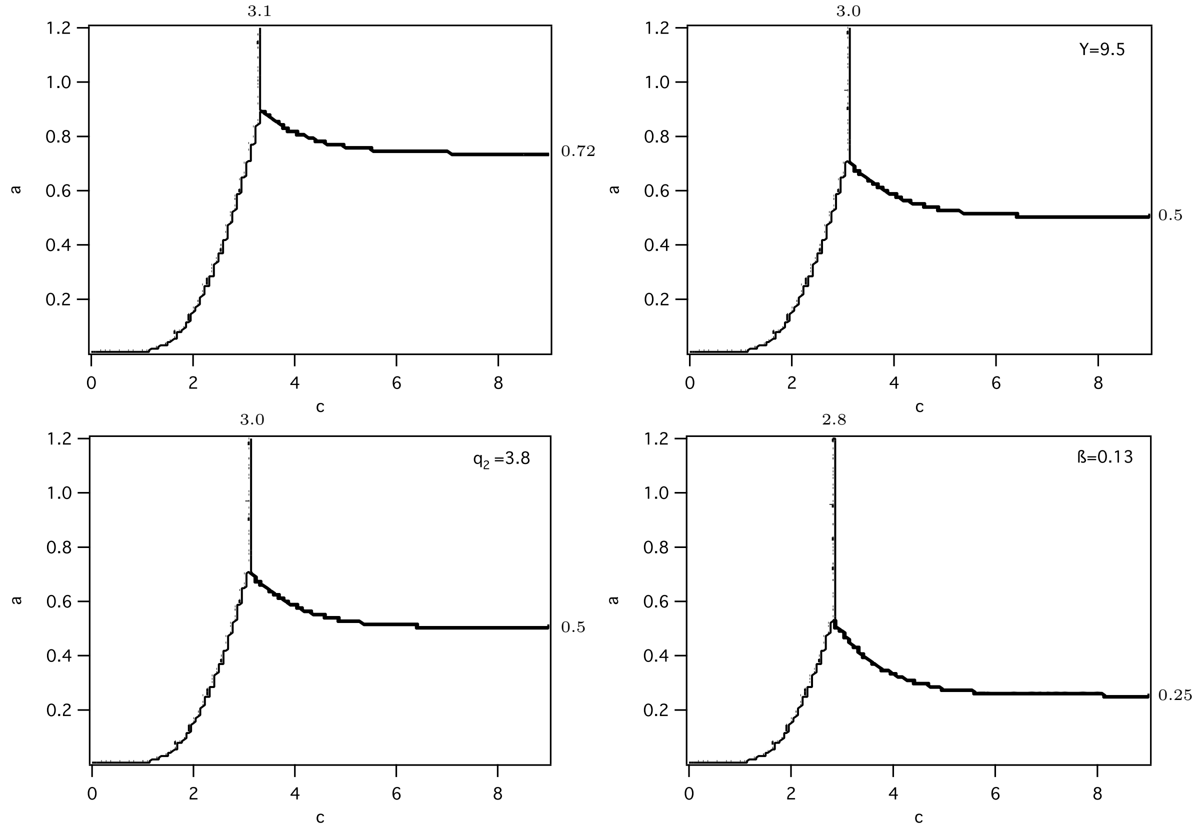

Figure 2: The effects of changes in Y, q_2 and β.

of demand from producer's old product (as the new product is a good substitute to the old product of the same firm, but not a good substitute to products traded on other submarkets). This indirectly increases the cost of innovation on own market. Therefore, the only available option is to innovate on remote submarkets (or not to innovate at all). However, when c is low consumers' baskets are more evenly balanced and innovating on own market affects the demand on producer's old product only marginally. In this case innovating on own submarket becomes an available alternative. The outcome is that interaction of these two forces (from supply and demand side) results in a pattern depicted in figure 1.

Changes of parameters besides c and a move borders between the regimes. The last four parameters in table 1 describe initial conditions, therefore we can not freely experiment with their values as changing them modifies the essence of the problem. The same goes for q_1, the value of which ensures that producers do not innovate without spending money. Out of remaining five parameters, γ does not have any impact on producer's problem as demonstrated earlier (equation (3)). As price and income only affect producer's problem through demand, looking at equation (8) suggests that increasing price will be equivalent to decreasing income. Hence, we discuss only the effect of one of them.

Figure 2 demonstrates the effect of changes in the three parameters to which producer's problem is sensitive: Y, q_2 and β. This is a robustness check for the results presented in figure 1. In figure 2, upper left panel is the same as figure 1. Upper right panel demonstrates the effect of decrease of consumer's income, Y (from 10 to 9.5). Lower left panel demonstrates the effect of the decrease of R&D productivity parameter q_2 (from 4 to 3.8). Lower right panel demonstrates the effect of decrease of share of profits invested in R&D, β (from 0.15 to 0.13). As one can clearly see all these changes affect the results only quantitatively (moving borders). Thus we can conclude that the division of *a*-*c* parameter space in three fractions as presented in figure 1 is a robust finding.

3.2.2 Equilibrium firm size distributions

As we argued before, the initial R&D incentives and sizes are equal across firms. But although every firm has an incentive to innovate (if we are not in R1), the success rate of this process is not 100%. It can be expected that only a certain (say α) fraction of all firms will come up with the new product. This introduces the heterogeneity among the firms. Firstly, firms are becoming heterogeneous in size: α fraction of firms now has two products on the market (each), while $1 - \alpha$ fraction is still producing only one product. Even more, as after innovation products will not be uniformly distributed over submarkets, the size of demand for one product will be potentially different from another. This implies that there will be heterogeneity even inside each of the groups (initial innovators and initial non-innovators). Secondly, there will be a heterogeneity in market knowledge (only in case of R3), those firms who innovated will acquire better knowledge about remote submarkets. Thirdly, there will now be a heterogeneity in further R&D incentives. This is due to heterogeneity in profits (size), in knowledge and also in non-uniform product distribution over submarkets. It is expected that incentives of some firms decrease (for instance of firms that did not innovate and whose nearby markets got populated with new products that led to the decrease of profits), while of others increase (for example of firms that innovated on remote markets and acquired new knowledge that increased their R&D productivity).

The structure of the present model is such that R&D incentives depend on the combination of total per period income and number of products available on the relevant submarkets. Thus, as our consumers' income is constant and while product space grows it is guaranteed that the additional demand for a firm, which comes with the new product on the market, decreases with time. As this demand is the only reward for costly R&D activity it is guaranteed that at some point it will become low enough for every firm to loose the incentive to invest in R&D. This, in turn, guarantees that the game reaches equilibrium in finite time. In this section we study these computed stochastic equilibria. More precisely, we analyze the resulting firm size distributions.

Here we are not interested in parameter constellations that result in R1, as firms size distribution will not change with time. R2 is also relatively not interesting. In this case everybody has the incentive to innovate on their own markets, which does not result in any additional knowledge. If this incentive does not change we depart from the initial distribution only temporarily: ultimately every firm places an exactly equal number of products on their submarkets. This means that firms will again be homogenous in size. But if the parameter values are close enough to the border with R3 increase in profits might result in change of incentives for the innovator firm: now it might be optimal to invest in remote markets. Thus, some portion of R2 (close to the border with R3) might, at some later stage, become part of R3, and at the end result in interesting time invariant firm size heterogeneity. The most interesting regime from the perspective of equilibrium firm size distributions is R3, where profits as well as knowledge base can be changed due to the innovation process. In this section we concentrate our attention only on parameter constellations that fall under R3.

We reformulate our game as an agent-based model, where every producer is solving the unique profit maximization problem (of course these problems coincide during $t = 0$). We set the parameter values as listed in table 1, choose the constellation of a and c that falls in R3 (as given in figure 1) and run the model for consecutive time periods until it reaches equilibrium. Then we examine the shape of the firm size distribution in computed time invariant state.

The general result is that in R3 the entry game produces equilibrium firm size distributions that are heavy-tailed and skewed to the right. Normality test introduced by Anderson and Darling (1952) is rejected in all the runs we performed[7] with a very high confidence level. Quantile-quantile plots of the generated data suggest that the right tail of the resulting firm size distribution is Pareto-type, which is consistent to numerous empirical findings for developed countries (Coad, 2009). Next we examine the relation of the shape of equilibrium firm size distribution and the values of a and c parameters. More precisely we try to understand the contribution of variations in these parameters towards the fatness of the tail.

There are many ways to measure the fatness of the tail of a Pareto-type distribution. The methodology most widespread in the extreme value statistics literature is the one proposed by Hill (1975). Estimation of Hill index requires the explicit specification of tail size or more precisely, where we consider that tail of distribution starts. The procedure was designed for Pareto distributions, in case of which the methodology produces unbiased estimate of the tail index no mater where the tail starts. However, if the distribution is not exactly Pareto, Hill index is biased and the result that we get is sensitive to tail size selection. This problem is

[7]Which is over a million runs for various parameter constellations

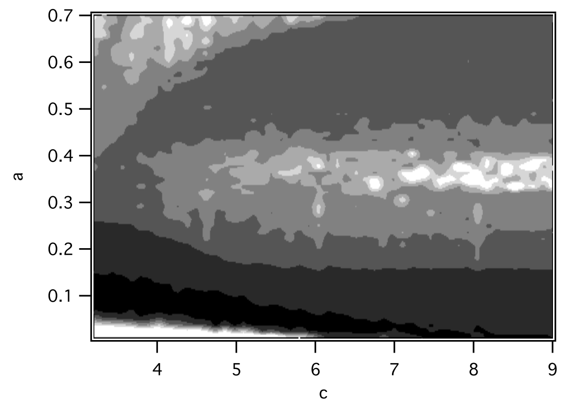

Figure 3: Hill indexes for the different parameter constellations.

especially acute in small samples. This points to the importance of a careful tail size selection in case of analysis of empirical or experimental data.

There are several procedures for selecting the tail size. In this paper we use one of the most efficient procedures of adaptive tail selection proposed by Beirlant, Dierckx, Goegebeur, and Matthuys (1999). More precisely, the simplification of Beirlant, Dierckx, Goegebeur, and Matthuys (1999) procedure proposed by Matthuys and Beirlant (2000). It selects the tail size by minimizing the asymptotic mean square error (AMSE) of the estimate. AMSE is additive in two parts: the variance of the estimate and the squared bias. It has been demonstrated that in small samples this procedure outperforms the alternatives for a large set of Pareto-type distributions (Matthuys and Beirlant, 2000).

There are alternative approaches to calculation of tail index. For example fitting a line to the Pareto quantile plots (Beirlant, Vynckier, and Teugels, 1996; Luttmer, 2007), moment estimators (Dekkers, Einmahl, and de Haan, 1989) or peak over threshold methods (Balkema and de Haan, 1974).[8] Like the usage of Hill estimator, each of these approaches has its disadvantages. These approaches are computationally more demanding and more suitable for testing for goodness of fit. As we are not trying to find the best fit to our data and in principle we are not even interested in the exact value of the tail index, but rather its dependence on model parameters, we opt for estimating the adaptive threshold and, consequently, Hill index.

The methodology is as folows. For each constellation of $c - a$ parameters in R3 we run the game until it reaches the equilibrium. To the data generated we apply the Matthuys and Beirlant (2000) procedure for tail selection and calculate Hill index. We repeat this 50 times and average Hill index over those 50 runs to obtain an estimate of tail index for a certain constellation.

The results for the relevant portion of R3 are presented in figure 3. Darker shades of grey represent fatter tails. In parts closer to the borders with other regimes results are noisy reflecting

[8]For a good summary of these approaches see Beirlant, Dierckx, Goegebeur, and Matthuys (1999).

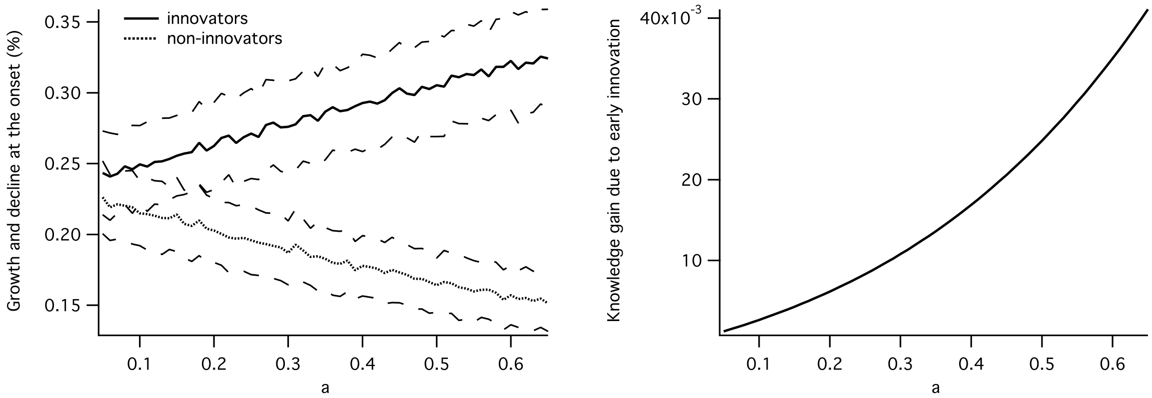

Figure 4: Changes in innovation incentives.

the regime change. However, in the interior of R3 Hill index profile is stable and it has a shape presented in figure 3. What we try to show on this figure is the qualitative relation between distribution tail and model parameters. We are not trying to draw the parallel between the magnitudes of tail indexes observed in reality and in our numerical exercise. The average of Hill index in our experiment is close to three, while real-life firm size data has been found to be fatter-tailed (index being slightly lower than two) (Coad, 2009).[9] Rather we are trying is to understand the contribution of the model parameters to the tail fatness of the actual firm size distributions.

The major finding in that respect is that in the interior of R3 thickness of the tail does not depend on demand parameter c: variation in tail index is explained by the variation in submarket specificity of producer knowledge (a).[10] We find that the dependance of the tail index on the relative knowledge productivity has the inverted U shape.

In order to understand the intuition note, that fatter tail means there are more firms of considerably larger size than the mean of the distribution. Due to the structure of the model, these are the firms who have more products on the market in equilibrium. As we do not have market for the intellectual property, bigger firms are also the most successful innovators. These are usually firms who were lucky to have successful R&D projects at the onset of the run. Consider the effects a successful innovation has on incentives to innovate for the innovator and for the competitors who were not successful at this period. For the innovating firm this has two positive effects on R&D productivity: its profits have increased (i) and its knowledge base has expanded (ii). There is also the third effect, that affects both innovators and non-innovators. This is creative destruction (iii). Recall that creative destruction is asymmetric in our model, hence depending on new product placement it will affect firms asymmetrically.

[9]However, changing the initial conditions change average values of Hill index (without changing the qualitative picture), thus the model can be calibrated if necessary.

[10]The similar behaviour as reported on figure 3 continues further for higher values of c.

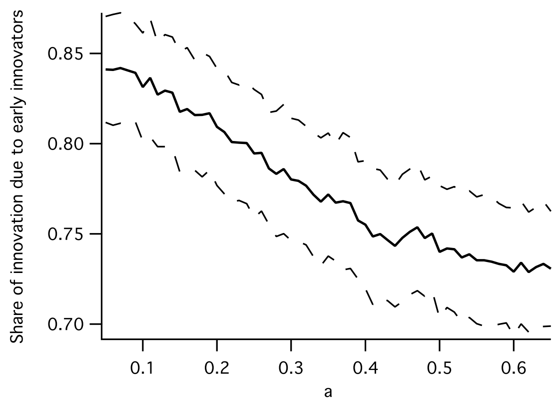

Figure 5: Changes in innovation freequency.

Consider how the size of the effect (i) varies with a. The left panel of figure 4 presents a statistical picture of what happens to the size of innovators and non-innovators after the first period. These are averages of 200 runs and respective standard deviation bands. We set value of c to be equal to $c = 9$, however, as we argued before, the results are not sensitive to the value of this parameter. Figure 4 shows the percentage growth of innovators and percentage decline of non-innovators. It says that when $a = 0.1$ a typical innovator grows by 25% during the first time period, while a typical non-innovator shrinks by 22%. One can easily see that these effects are linear in a, thus the difference between them (which is the measure of the difference in incentives to innovate between two groups) is also linear. The difference between these two values is slightly growing in a.

Now consider the size of the effect (ii). To measure the new knowledge acquired by innovative firms we can calculate the integral of their knowledge over the submarkets at period $t = 0$ and at period $t = 1$ and take the difference. Non-innovators do not gain any new knowledge. Note that as firms are homogenous at $t = 0$ we do not require statistical approach, we can calculate the value of the effect (ii). Right panel of figure 4 plots this value. One can see that it is increasing at higher rates with increasing a. Thus, this measure (as measure (i) above) suggests the explanation for the fatter tails when the value of a is high: innovation during the first period gives higher knowledge gain and higher incentives for further innovation. However, it does not offer the explanation for the fatter tails when the value of a is in lower range.

The reason for fatter tails in lower ranges of a can be found in the dependence of value of the effect (iii) on a. But there is no comprehensive way of measuring this effect. This effect is too sensitive to location of new products and attempts to measure it produce very noisy results. However, we can employ the statistical approach again and estimate the total difference in innovation incentives between early innovators and non-innovators. We can simply track the two groups until the equilibrium and record all the subsequent innovations. Then we can take the number of later innovations per early innovator and number of later innovations per early non-innovator and study the dependence of their difference on a. This measure simply looks at the realized innovation, thus takes all three effects into account.

Figure 5 plots the share of innovation due to early innovators (as average of 200 runs) and standard deviation band. As one can see even though for lower values of a knowledge gain is small and that the size of the effect (i) is relatively low, early innovators obtain higher invectives to continue innovation than for higher values of a. This should be the effect of the creative destruction (effect (iii)) that we cannot measure. The value plotted in figure 5 goes down steadily with increasing a, thus the difference in innovation frequency between a typical innovator and non-innovator is lower for higher values of a. However, innovations by innovators are better positioned in taste space as they possess good knowledge.

Therefore, we can conclude, that fatter tails for low values of a are due to higher innovation frequency by early innovators, however fatter tails for higher values of a are due to the considerable knowledge gain by early innovators. From figures 4 and 5 one can see that the size effect on innovation incentives is linear in a, the frequency of innovation in falling at somewhat decreasing rate and, most importantly, knowledge is growing at an increasing rate. Therefore, interaction of these three effects creates relatively thin tails for intermediate values of a.

Notice that parameter a is an industry level parameter. Thus, the shape of Hill index profile is an empirically testable result: one can look at the different industries, measure submarket specificity of their knowledge and tail indexes of firm size distributions and see if the relationship has and inverted U shape. However, there are several issues with this procedure: it requires high quality data, it also calls for the control of other differences across industries. Most importantly, it is not very clear how one can measure submarket specificity of producer market knowledge in various industries on a comparable scale.

4 Summary and Conclusion

In this paper we have analyzed a simple boundedly rational model of producer behaviour in which heterogeneity of knowledge, R&D behaviour and firm size is generated endogenously. We have considered two key parameters of the model: submarket specificity of consumer tastes and submarket specificity of producer knowledge. We have studied the effects of these parameters on the R&D incentives at the onset of the industry populated by homogenous firms. Depending on parameter constellations we have identified three regimes in which optimal behaviour of a typical firm is qualitatively distinct: (i) no R&D, (ii) R&D only on familiar markets (no diversification) and (iii) R&D on unknown markets (diversification).

We have also analyzed the equilibrium firm size distributions which are the result of industry evolution in the regime where there are incentives to diversify. It turns out that the resulting firm size distributions are fat tailed and positively skewed, which is in accordance with what has been found empirically. Results indicate that for the interesting segment of parameter values the thickness of the tail of firm size distribution depends only on producer knowledge specificity parameter of the industry.

The conclusion is that successful innovation has has two positive effects on innovators. Firstly, their profits increase. Secondly, their knowledge base increases. Both of these contribute to higher productivity of future R&D. On competitive constant size markets product innovation by a firm also has a negative effect. Due to Schumpeterian creative destruction new product reduces shares of incumbents. This negative effect influences innovators as well as non-innovators. Interplay of all these forces contributes to the shaping of industry's firm size distribution as a fat tailed one. Therefore, looking at actual R&D behavior and at its effects on firms in certain industries can shed light to the process of emergence of actual fat tailed distributions.

References

Anderson, T. W., and D. A. Darling (1952): "Asymptotic Theory of Certain "Goodness of Fit" Criteria Based on Stochastic Processes," *The Annals of Mathematical Statistics*, 23(2), 193–212.

Andrews, K. R. (1971): *The concep of corporate strategy.* Dow Jones-Irwin, Homewood, IL.

Arrow, K. (1962): "Economic welfare and the allocation of resources for inventions," in *The rate and direction of inventive activity*, ed. by R. R. Nelson, pp. 609–626. Princeton University Press, Princeton, NJ.

Balkema, A., and L. de Haan (1974): "Residual life at target age," *Annals of Probability*, 2, 792–804.

Beirlant, J., G. Dierckx, Y. Goegebeur, and G. Matthuys (1999): "Tail index estimation and an exponential regression model," *Extremes*, 2(2), 177–200.

Beirlant, J., P. Vynckier, and J. L. Teugels (1996): "Tail index estimation, pareto quantile plots, and regression diagnostics," *Journal of the American Statistical Association*, 91(436), 1659–1667.

Cabral, L. M. B., and J. Mata (2003): "On the Evolution of the Firm Size Distribution: Facts and Theory," *The American Economic Review*, 93(4), 1075–1090.

Coad, A. (2009): *The growth of firms: A survey of theories and empirical evidence.* Edward Elgar.

Cohen, W. M., and S. Klepper (1992): "The Anatomy of Industry R&D Intensity Distributions," *The American Economic Review*, 82(4), 773–799.

Cohen, W. M., R. C. Levin, and D. C. Mowery (1987): "Firm Size and R&D Intensity: A Re-Examination," *The Journal of Industrial Economics*, 35(4), 543–565.

Cohen, W. M., and D. A. Levinthal (1989): "Innovation and learning: Thte two faces of R&D," *Economic Journal*, 99, 543–563.

de Wit, G. (2005): "Firm size distributions: An overview of steady-state distributions resulting from firm dynamics models," *International Journal of Industrial Organization*, 23(5-6), 423 – 450.

Dekkers, A., J. Einmahl, and L. de Haan (1989): "A momend estimator for the index of an extreme value distribution," *Annals of Statistics*, 17, 1833–1855.

Gibrat, R. (1931): *Les inégalités économiques.* Recueil Sirey, Paris.

Harris, C., and J. Vickers (1985): "Perfect Equilibrium in a Model of a Race," *The Review of Economic Studies*, 52(2), 193–209.

Hill, B. M. (1975): "A simple general approach to inference about the tail of a distribution," *The Annals of Statistics*, 3(5), 1163–1174.

Kalecki, M. (1945): "On the Gibrat distribution," *Econometrica*, 13(2), 161–170.

Klette, T. J., and S. Kortum (2004): "Innovating Firms and Aggregate Innovation," *The Journal of Political Economy*, 112(5), 986–1018.

Lancaster, K. (1979): *Variety, Equity, and Efficiency.* New York: Columbia University Press.

Luttmer, E. G. J. (2007): "Selection, growth and size distribution of firms," *Quarterly Journal of Economics*, 122(3), 1103–1144.

Matthuys, G., and J. Beirlant (2000): "Adaptive threshold selection in tail index estimation," in *Extremes and Integrated Risk Management*, ed. by P. Embrechts, pp. 37–49. Risk Books, London.

Nelson, R. R. (1982): "The Role of Knowledge in R&D Efficiency," *The Quarterly Journal of Economics*, 97(3), 453–470.

Nelson, R. R., and S. G. Winter (1982): *An evolutionary theory of economic change.* Belknap, Cambringe, MA.

Porter, M. E. (1980): *Competitive strategy: Techniques for analyzing industries ad competitors.* Free Press, New York, NY.

Silverberg, G., and B. Verspagen (1994): "Collective Learning, Innovation and Growth in a Boundedly Rational, Evolutionary World," *Journal of Evolutionary Economics*, 4(3), 207–26.

Simon, H. A. (1955): "On a class of skew distribution functions," *Biometrika*, 52, 425–440.

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