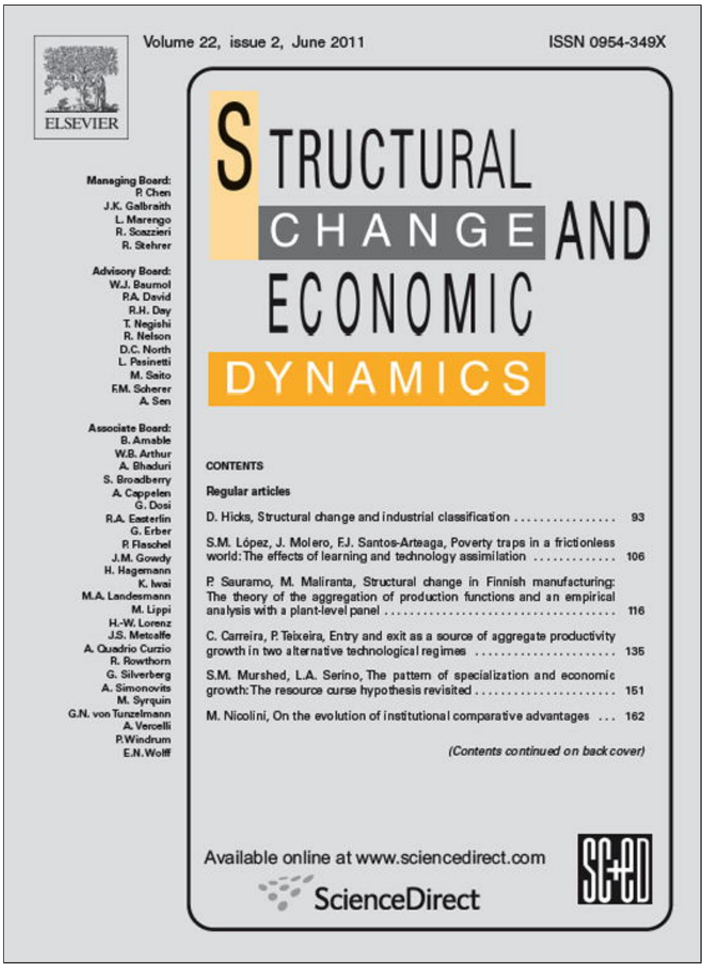

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Entry and exit as a source of aggregate productivity growth in two alternative technological regimes

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ABSTRACT

This paper proposes a neo-Schumpeterian model in order to discuss how the mechanisms of entry and exit contribute to industry productivity growth in alternative technological regimes. Our central hypothesis is that new firms generate gains in aggregate productivity by increasing both the productivity level and competition intensity. By assuming that firms learn about the relevant technology through a variety of sources, and by allowing a continuous flow of entry and exit into the market, our study shows that firm exit and output contraction take mostly place among less productive firms, while output expansion and entry are concentrated among the more efficient ones. The greater is the competitive pressure generated by new entrants, the higher is the expected productivity level of established firms. Overall, our analysis suggests that micro analysis is the proper complement to aggregate industry studies, as it provides a considerable insight into the causes of productivity growth.

1. Introduction

In the past few years the study of productivity issues has greatly shifted towards the understanding of the operation of micro units, with a particular emphasis on establishment- (and firm-) level reallocation. It has been shown in particular that a large percentage of industry productivity growth can be imputed to mobility of firms, with low-productivity firms losing market share (or shutting down) in favour of more productive incumbents and new entrants (Carreira and Teixeira, 2008; Foster et al., 2001). Furthermore, as shown by Aghion et al. (2009) and Falck et al. (forthcoming), the contribution of new firms to aggregate productivity growth is not only a direct one (through higher productivity than incumbents), but also indirect, via an increase in competitive pressure.

In order to provide a better understanding of the effects of new firms on productivity growth, this study proposes a neo-Schumpeterian model in which the role of firm dynamics on the evolution of a *mature* industry is extensively modelled. In a new departure from the original Nelson–Winter evolutionary industry model (Nelson and Winter, 1982; Winter, 1984), which was mostly focused on technological change, we examine how the entry and exit contribute to industry productivity growth. A central assumption in our approach is that there are two potential channels through which new firms have an impact on productivity growth: a direct one, as new firms may be relatively more productive than incumbents; and an indirect one, as new firms may generate a higher level of competition. We show that the competitive pressure induced by new firms generate sizeable firm reallocation and, as a consequence, a higher aggregate productivity. Surely, these effects would not be possible to be analyzed within a simple framework of a representative firm in which the productivity level is, by definition, common across firms.

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Another key aspect of our modelling is the full characterization of the technological regime in which firms operate.[1] As in Winter (1984), two basic cases are considered: the 'routinized regime' and the 'entrepreneurial regime'. Analytically, the difference between these two regimes is modelled via two main aspects: (a) innovative draws, which are based on firm's current productivity level—in the routinized regime—or as a function of industry's average productivity—in the entrepreneurial regime; and (b) entry and exit, with entry rates being set at a lower level in the routinized than in the entrepreneurial regime, and the productivity level of entrants based on the industry average—in the routinized regime—or on the industry's best practice—in the entrepreneurial regime. Empirically, the distinction between the two regimes has been confirmed by Malerba and Orsenigo (1996), for example, who, using patent data of six countries (US, Japan, Germany, France, the UK, and Italy), found that 19 out of 49 technological classes show patterns of entrepreneurial regime, while 15 out of 49 can be characterised as routinized regime (see also Breschi et al., 2000; Malerba and Orsenigo, 1995).

We develop a competitive dynamic setting of a *mature* industry (in a *developed market economy*) in which we have a continuing flow of heterogeneous firm entry and exit. Following the taxonomy proposed by Malerba (1992), firms can learn through 'learning by doing' and 'learning by using', on the one hand, and 'learning by searching' and 'learning from external sources', on the other. Moreover, as in Nelson and Winter (1982), firms compete with a homogeneous product through costs reduction, which is achieved through productivity improvements. In other words, in our modelling firms are focused on *process* innovation. Alternatively, one can think in terms of *product* innovation in which single-product firms compete through (vertical) product differentiation—assuming that one unit of the product contains a given amount of the single Lancasterian characteristic.[2]

In order to analyse the main properties of the model, we first introduce a non-stochastic version with no learning. Then, we discuss how the numerical results fit some key stylized facts and how the entry contributes to industry productivity growth. Our findings show that exit and output contraction take mostly place among less productive firms, while entry and expansion are concentrated among high-productivity firms. Moreover, much of the market share variation can be connected to higher competitive pressure brought in by new firms which force the least productive firms to exit. We also find that a higher entry rate of new firms is positively associated with a higher productivity level of incumbent firms.

2. Firm dynamics and industry productivity growth: some facts

Studies in several countries indicate that entry and exit flows of firms are very substantial (Caves, 1998; Geroski, 1995). In the U.K. manufacturing sector, for example, the (annual) entry and exit rates were about 6.5% and 5.1%, respectively, in the period 1974–1979. In Canada, between 1970 and 1982, the corresponding rates were 4.9 and 6.5%. Moreover, these rates vary substantially across industries—for example, the entry rate fluctuated from 3.5% to 9.6% across the U.K. (two-digit) sectors.

Entry and exit also tend to be highly positively correlated. The main reason is of course that the rate of early mortality is very high for entrants. In Canada, the hazard rate for 1971 entrants was about 10% at the end of the first year (roughly, twice as much as for the incumbent firms). In the U.K., 19% of new firms established in 1974 exited within the following 2 years, while 51% did not survive longer than 5 years (Baldwin, 1995; Geroski, 1991).

In contrast, the growth rate among successful entrants is very high. On average, surviving new plants double their initial size after 6–7 years (Mata et al., 1995), although successful entrants may take more than a decade to achieve the average size of established firms (Audretsch and Mata, 1995).[3]

The relationship between industry dynamics and firm characteristics (e.g. size, age, technological environment, and innovation) is also an important one (Caves, 1998; Geroski, 1995). The technological environment, for example, seems to impact the entry rate, while profits do not (Dosi and Lovallo, 1997; Geroski, 1994). Acs and Audretsch (1990) and Geroski (1994) have observed indeed a positive (although modest) correlation between entry and innovation rates, suggesting that a more innovative environment encourages entry. Entry also seems to be more intense in an environment providing potential entrants with greater opportunities to innovate, while the greater is the total amount of innovative activity and intensity of R&D, the higher seems to be the entry barriers.

Audretsch and Acs (1994) note, in particular, that the entry rate is lower in prototypal routinized regime industries than in industries in which the entrepreneurial regime seems to be the dominant pattern.[4]

The influence of technological environment and innovation on the ability of new firms to survive has also been examined in the literature. Audretsch (1991), using the United States data on new (i.e. created in 1976) manufacturing firms, found that an increase in the capacity of small and new firms to innovate leads to a higher survival rate, especially in the entrepreneurial regime. In the routinized regime, where the ability of small firms to innovate is relatively low, the survival rate tends to be smaller. Another important regularity is that firm's growth rate decreases with size and age, while survivability increases with the same arguments (Evans, 1987).

The technological environment influences market turbulence (or market share instability) as well (Dosi et al., 1995). For U.S. firms (1976–1980), Audretsch and Acs (1990) found that turbulence was higher in industries char-

[1] Technological regimes are defined by Nelson and Winter (1982) as the technological environment of an industry under which firms operate.

[2] For a model with product differentiation, see, for example, Marengo and Valente (2010) in this journal.

[3] An entrant is typically very small. In the United States, for example, an entrant (over the period 1963–1982) only produces in the entry year 35.2% of the incumbents' output level, on average (Dunne et al., 1988).

[4] The full definition of technological regimes is given in Section 3.

acterised by the entrepreneurial regime. Turbulence was indeed higher in industries where small firms were able to implement a strategy of innovation and lower in industries where they were less able to innovate. Davies and Geroski (1997) in turn observed that turbulence in the top five U.K. firms (in 1979 and 1986) tend to increase with R&D intensity, but the characteristics of this specific sample of firms make the comparison a difficult one. Surprisingly enough, Audretsch and Acs (1990) found that there is more, not less, turbulence in concentrated industries.[5]

Finally, the dynamics of firms is expected to lead to a higher aggregate productivity growth, with changes in industry-level productivity arising either from within-firm productivity growth (for example, due to technological changes or human capital improvements), or from resource reallocation (i.e. entry and exit of firms). Baily et al. (1992), for example, found that the contribution of increasing (decreasing) output shares of high- (low-) productivity continuing plants was the most important source of the U.S. industry productivity growth, while the entry-exit effect was found to be very small. For its part, Foster et al. (2001) found that net entry plays a significant role in the medium and long term, with resource reallocation accounting for half of manufacturing productivity growth, of which about 18% was due to the net entry effect. These results were corroborated by Baldwin (1995) who has shown that, in the 1970s, firm dynamics contributed substantially to the Canadian (labour) productivity growth—around 40–50% of productivity growth was estimated to have been due to firm dynamics, with 37% of the employment share being reallocated from exiting and contracting plants to entering and expanding plants (see also Baldwin and Gu, 2006; Cantner and Krüger, 2008; Carreira and Teixeira, 2008; Disney et al., 2003; Foster et al., 2001). However, all these results are based on widely used decomposition methods of aggregate productivity growth that yield biased contributions of entrants (Hyytinen et al., 2010; Melitz and Polanec, 2009; Maliranta, 2009). Furthermore, they focus on entry direct effect, while the main contribution of entrants may be an indirect one. As shown by Aghion et al. (2009), Carreira and Teixeira (2010) and Falck et al. (forthcoming), the indirect impact (via de competitive pressure) on aggregate productivity growth can be even larger.

3. The model

The empirical regularities outlined in the previous section provide the background and the motivation for our modelling strategy. Our model draws on Nelson–Winter evolutionary industry model (1982: ch. 12; Winter, 1984), with two main novelties: (a) a greater focus on the learning process, namely we assume that firms can improve technologically through a variety of sources: ‘learning by doing’, ‘learning by using’, ‘learning by searching’, and ‘learning from external sources’ (Malerba, 1992); and (b) detailed analysis of entry and exit.

[5] For a given concentration index, more turbulence suggests the presence of a higher degree of competition.

Let us assume all technologies exhibit constant returns to scale, with output equal to full capacity. Input supplies are perfectly elastic and input prices are exogenously given and constant over time.[6] At time ‘zero’, a ‘mature’ industry made up of a finite number of competitors producing a single and homogeneous product. Alternatively, one can think in terms of product differentiation where one unit of output that contains a given amount of a single Lancasterian characteristic is supplied by a producer operating in monopolistically competitive industry. Suppose that from the point of view of consumers the marginal value of a given Lancasterian characteristic is a perfect substitute for price reduction, then form the point of view of producers is equivalent of a reduction of marginal cost of production this Lancasterian characteristic (see note 8).

Fig. 1 gives the main structure of the model. In each period the state of production technologies across firms determine the output level and the market price. Then, once firms R&D investment is made, and assuming their R&D activities are successful in innovating or imitating, they decide whether to stick with the current technology or engage on technological changes in the next period. Once firms learn about their performance, they then decide on the future R&D effort and whether to continue or exit, while new firms enter in the market.

3.1. Production, costs and profits

Given product homogeneity, firms choose quantities rather than prices. Quite naturally, more productive firms (i.e. with a competitive cost advantage) are expected to gain market share, while less productive firms will be expected to lose market share (or forced to exit).

In particular, the production level of firm i at time t, $i \in I = \{1, \ldots, n_t\}$, is given by:

$$q_{it} = q_{i(t-1)}(1 + g_{it}^{q}), \quad (1)$$

where g_{it}^{q} is the Metcalfe (1998: ch. 2) version of the ‘replicator dynamic’, defined as (assuming a zero growth rate for the entire market demand)[7]:

$$g_{it}^{q} = \delta_i \left(1 - \frac{c_{it}}{\bar{c}_{(t-1)}}\right), \quad (2)$$

where c_{it} denotes the production cost per unit of output of firm i at time t, $\bar{c}_t$ is the average of the firms' unit costs weighted by the corresponding market share s_{it}, with $\bar{c}_t = \sum_{i=1}^{n_t} s_{it} c_{it}$ and $s_{it} = q_{it}/Q_t^S$. δ_i is an upper bound on firm's growth and can be interpreted as a firm's financial constraint (Cabral and Mata, 2003; Cooley and Quadrini, 2001; Oliveira and Fortunato, 2006) or as an intensity measure of the selection mechanism (Metcalfe, 1998). Clearly,

[6] These assumptions are also made in original Nelson–Winter model and follow the strand of industrial organization models.

[7] The replicator dynamic equation was originally introduced into mathematical biology by R.A. Fisher. It was Silverberg (1987) who extended it to competition among firms. Silveberg's replicator equation relates each firm's market share to the difference between firm's competitiveness and the industry-wide level of competitiveness (see also Silverberg, 1988). In the Metcalfe model, the growth rate depends on the absolute difference between individual unit costs and the corresponding industry average.

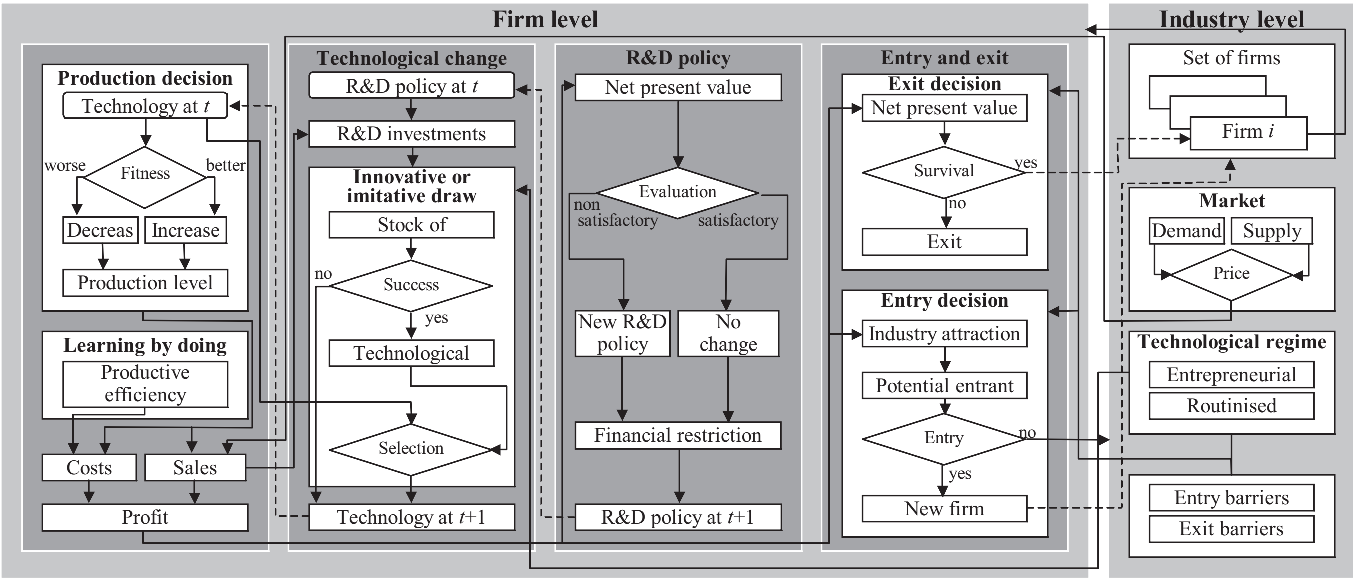

Fig. 1. Structure of the model.

given Eq. (1), $q_{it} = 0$ if $g^q_{it} = -1$. In turn, the higher is δ, the stronger is the adjustment mechanism. Within this context, a firm's growth rate is higher (lower) than the market average if its unit cost is lower (higher) than the average cost of the established firms in $t-1$.

In each period, firm i is characterised by a 'Leontief production function'[8]:

$$q_{it} = \min(a^1_{it}x^1_{it}, \ldots, a^m_{it}x^m_{it})u_{it}, \tag{3}$$

where q_{it} is firm's output at time t, x^j_{it} is firm's demand of the jth input ($j \in J = \{1, \ldots, m\}$), a^j_{it} ($a^j_{it} > 0$) is the productivity of input j (i.e. the amount of output produced per unit of input j under maximum efficiency), and u_{it} is an index of firm's production competence in the use of its technique, given by firm's productive efficiency level at time t (i.e. $u_{it} = q_{it}/q^{Max}$, where q^{Max} represents the best-practice of firm's technique; $0 < u_{it} \leq 1$).

The unit production cost of this constant returns to scale technology (then, the marginal cost) is given by:

$$c_{it} = \frac{1}{u_{it}}\left(\sum_{j=1}^{m}\frac{w^j}{a^j_{it}}\right), \tag{4}$$

where w^j is the unit price of the jth input. In this framework, a change in firm's unit cost arises either from changes in a^j_{it} or from changes in u_{it}. When a^j_{it} (or u_{it}) increases, the unit cost decreases, as $\partial c_{it}/\partial a^j_{it} = -w^j(u_{it})^{-1}(a^j_{it})^2 < 0$ and $\partial c_{it}/\partial u_{it} = -(u_{it})^{-2}\sum_{j=1}^{m} w^j(a^j_{it})^{-1} < 0$.

Industry output at time t is given by the sum of the firms' output levels:

$$Q^S_t = \sum_{i=1}^{n_t} q_{it}. \tag{5}$$

We assume that the industry faces a decreasing continuous (inverse) demand function:

$$P_t = D(Q^D_t), \tag{6}$$

where P_t is the market price and Q^D_t denotes the market demand at time t, with $\lim_{Q^D_t \to 0} D(Q^D_t) < \infty$ and $\lim_{Q^D_t \to \infty} D(Q^D_t) = 0$. As in the original Nelson–Winter model, and to avoid introducing further assumptions on the nature of the produced good, it is assumed an homogeneous commodity.[9] In each period, equilibrium in the product market determines the market price at time t, that is, $P_t = D(Q^S_t)$.

The profit of firm i at time t is equal to total sales minus production and R&D costs:

$$\pi_{it} = [(1 - r_{it})P_t - c_{it}]\, q_{it}, \tag{7}$$

where r_{it} is the R&D expenditure rate per unit of sales ($0 \leq r_{it} < 1$).

[8] We note that the Nelson and Winter model (1982: ch. 12) assumes Leontief technologies, with each firm i at time t using the inputs in a given proportion. The techniques in the Nelson and Winter model are thus characterised by Hicks' neutral technical changes, with technical progress leading to proportional reductions in all inputs. In our case, although we assume a Leontief technology, we will allow for differences in productivity changes across inputs over time.

[9] An alternative heterogeneous commodity interpretation is that product i differ on the amount of a single Lancasterian characteristic, the quality i. Assuming its marginal value a perfect substitute for price reduction from the point of view of consumers, the consumer will only care about the "real price" $P_t = p_{it} - s_i$, with p_{it} denoting the price of the product at quality i and s_i the (monetary) marginal value of quality i. The demand function for q_{it} units of product i is $q_{it} = Q(p_{it} - s_i)$, so that the inverse demand function is aditive in s_i: $p_{it} = D(q_{it}) + s_i$. Then form the point of view of producers is also equivalent of a price reduction or a marginal cost reduction of the production the product at quality i, c_{it}: $P_t + s_i = c_{it} \Leftrightarrow P_t = c_{it} - s_i$; that is, as in Eq. (4). For a model with product differentiation, see, for example, Marengo and Valente (2010) in this journal.

3.2. The learning process

Learning and adapting over time is a key aspect to survivability, but routines are usually hard to change, and are responsible for inflexibility and inertia in organisational behaviour. Routines do change, however, as new knowledge is incorporated within the transmission of firm's knowledge over time (Metcalfe, 1998).

Firms can learn through a diversity of sources of knowledge. Following Malerba (1992), we assume different types of firm's learning: 'learning by doing' and 'learning by using' (i.e. 'learning' that emerges from production activity and from the use of products, machinery, and inputs), 'learning from advances in science and technology' and 'learning from inter-industry spillovers' (i.e. 'learning' resulting from the exploitation of external sources of knowledge), and 'learning by searching' (i.e. 'learning' that is related to research made within the firm). As described below, in our model firms can improve their productivity level via one of these three channels.

We formally model the learning process through two mechanisms: (a) *productive efficiency* gains in the use of the technology via variations in u_{it}; (b) *technological changes* via variations in production parameters a_{it}^j by innovation or imitation. Furthermore, it is assumed that improvements in the technological level are always achieved through learning (*disembodied* change), and not by investments in new, more productive equipment (*embodied* change). In other words, an improvement in technology always corresponds to a better knowledge of the production process, not to a replacement of the capital stock.[10]

Efficiency gains in the use of production technology result in our model from 'learning by doing' and from 'learning by using', and are modelled as a continuous and cumulative process rather than the result of any direct R&D activity. We consider however that the two selected types of learning are conditioned in the following way: (a) the learning process is limited by the maximum efficiency of the technique used (i.e. the best-practice); (b) when a new technology is introduced the previous productive knowledge is partly discarded (the technology-specific knowledge component). Formally, u_{it} can be written as the following logistic function:

$$\begin{cases} u_{it} = 1 - e^{-\nu_{ik}\tau_{ik}} & \text{if } \tau_{ik} > 1 \\ u_{it} = \varepsilon_{it} \cdot u_{i(t-1)} & \text{if } \tau_{ik} = 1 \end{cases}, \tag{8}$$

where τ_{ik} is the number of periods during which firm i uses the technology k, and ν_{ik} is a firm-specific parameter that denotes the learning speed and ε_{ik} is a random variable $(0 < \varepsilon < 1)$. A smaller value of ν_{ik} implies a slower learning process.

Before describing the technological changes through variations in production parameters a_{it}^j, which are obtained via innovation or imitation, we need to characterize two main alternative *technological regimes*. Indeed, we consider the concept of 'technological regime' as the key tool to understanding innovative activity (Breschi et al., 2000; Malerba and Orsenigo, 1995, 1996). Two kinds of Schumpeterian regimes are thus distinguished: (a) the entrepreneurial regime, a 'science-based' technology regime relatively favourable to new and innovative firms; (b) the routinized regime, a 'cumulative' technological regime that facilitates innovation from (large) established firms (Nelson and Winter, 1982; Winter, 1984).[11] In the entrepreneurial regime, the improvements in the current state of technological knowledge are mainly due to the new firms, while in the routinized regime such improvements are mostly associated to the established ones. In the 'science-based' technology regime, firms accumulate their own technological knowledge base from sources of knowledge external to the firm (for example, from public research institutions and from industry spillovers), and therefore technology is characterised by a broad and universal knowledge base. In the 'cumulative' technological regime, however, the sources of knowledge are internal to the firm and as a consequence the barriers to entry tend to be substantially higher. The difference between these two regimes is at first formally reflected in the model through the innovative draws within technological change process. In the routinized regime, as in Winter (1984), the innovative draws are based on the firm's current productivity level, while in the entrepreneurial regime are based on the industry's average productivity. The difference between the two regimes is also reflected in the entry and exit mechanisms of the model (Section 3.4). The entry rates are lower and exit barriers higher in the routinized regime than in the entrepreneurial regime and the productivity level of new firms is based on the industry average productivity in the former regime and on the best practice observed in the industry in the latter case.

As mentioned, the more productive technologies are obtained either by innovating new production processes or by mimicking the pre-existing ones. Following again the taxonomy introduced by Malerba (1992), in the former case, established firms adopt a 'learning by searching' process which is related to internal R&D activities (routinized regime) or a 'learning from advances in science and technology' (entrepreneurial regime); in the latter, firms adopt a 'learning from inter-industry spillovers' process, which is external to the firm, but related to current industry specific knowledge. The capacity of a firm to absorb external knowledge also depends on its R&D activities ('absorptive capacity of firms', after Cohen and Levinthal, 1989, 1990).

R&D investments are an increasing function of sales and they can be either innovative (R_{it}^N) or imitative (R_{it}^M), as fol-

[10] For a model with vintage capital, see, for example, Silverberg et al. (1988). In our case, we assume that the capital stock is fully transferable from one technology to another.

[11] These two regimes are often referred to as 'Schumpeter Mark I' and 'Schumpeter Mark II' (Malerba and Orsenigo, 1995), by analogy with Schumpeter's conceptions of the innovative firms developed in *The Theory of Economic Development* (1934) and in *Capitalism, Socialism and Democracy* (1942). Malerba and Orsenigo (1995, 1996, 2000) argue that a technological regime can be seen as a combination of the following properties of technologies: opportunity conditions, cumulativeness conditions, appropriability conditions and knowledge base.

lows:

$$\begin{cases} R_{it}^N = \alpha_i r_{it} P_t q_{it} \\ R_{it}^M = (1-\alpha_i) r_{it} P_t q_{it} \end{cases}, \tag{9}$$

where α_i is a firm-specific parameter denoting the share allocated to innovation, $0 \leq \alpha_i \leq 1$ (if α_i is near to 1, the firm is a strong innovator), and r_{it} is the R&D expenditure rate.

The quality (i.e. the probability of success) of R&D activities depends on both past and current R&D investment. Innovative and imitative knowledge are then accumulated as follows:

$$\begin{cases} Z_{it}^N = \theta_i^N Z_{i(t-1)}^N + (1-\theta_i^N) R_{it}^N \\ Z_{it}^M = \theta_i^M Z_{i(t-1)}^M + (1-\theta_i^M) R_{it}^M \end{cases}, \tag{10}$$

where Z_{it}^N and Z_{it}^M are the innovative and imitative stock of knowledge of firm i at time t, respectively, and θ_i^N and θ_i^M are firm-specific parameters weighting past research ($0 < \theta_i^N < 1$ and $0 < \theta_i^M < 1$).

We have modelled technological change as a three-stage process. The first stage determines whether a firm's R&D activities result in innovation or imitation in the current period. This is established by random variables d_N and d_M (the subscripts N and M denote innovation and imitation, respectively) which is equal to one (success) or zero (failure). A firm's probability of success in innovation/imitation is an exponential function of the stock of knowledge:

$$\begin{cases} Pr(d_N = 1) = 1 - e^{-b_N Z_{it}^N} \\ Pr(d_M = 1) = 1 - e^{-b_M Z_{it}^M} \end{cases}, \tag{11}$$

where b_N and b_M are industry-specific exogenous parameters of technological opportunities for innovative and imitative success, respectively. The use of the logistic function mirrors the assumption of decreasing returns of knowledge (and, then, R&D investments).

In the second stage, if a firm is successful in innovating ($d_N = 1$), the resulting input productivities are determined by a log normal distribution with a log mean μ_{it}^j and standard deviation σ, that is:

$$\ln a_{it}^{jN} \sim N(\mu_{it}^j, \sigma^2). \tag{12}$$

In the routinized regime, the innovative draws are based on the current input productivity level of the firm, which means that each firm follows its own technological path. Thus, the log mean is given by $\mu_{it}^j = \ln[(1+g_{it}^j)a_{it}^j]$, where g_{it}^j ($g_{it}^j > 0$) is the rate of productivity growth associated with innovation and it is stochastically determined. In the case of the entrepreneurial regime, the more productive technologies are obtained from an innovation process that depends mostly on external sources of knowledge (from advances in science and technology), that is, the technology is mostly non-cumulative. Therefore, the log normal distribution is here centred around the industry's average productivity in the period $t-1$, that is, $\mu_{it}^j = \ln[(1+g_{it}^j)\bar{a}_{i(t-1)}^j]$, where $\bar{a}_t^j = \sum_{i=1}^{n_t} s_{it} a_{it}^j$ is the average industry input productivity weighted by the corresponding market shares.

A successful imitation ($d_M = 1$) means that the firm learns about a subset of past production techniques available in the industry (i.e. it selects the best practice among the known technologies by the firm). Formally, the firm chooses the technique with the lowest unit production cost among a random subset:

$$\tilde{c}_t^M = \min(\tilde{c}_{(h-l)(t-1)}; \ldots; \tilde{c}_{h(t-1)}; \ldots; \tilde{c}_{(h+l)(t-1)}), \tag{13}$$

where $\tilde{c}_{ht} = \sum_{j=1}^m w^j / a_{ht}^j$, $h \in I$.

Finally, the firm has to choose, for the next period, between $\tilde{c}_{it}^N$, $\tilde{c}_t^M$ and the current technique, $\tilde{c}_{it}$, given by:

$$\tilde{c}_{i(t+1)} = \min(\tilde{c}_{it}; \tilde{c}_{it}^N; \tilde{c}_t^M), \tag{14}$$

where $\tilde{c}_{it}^N = \sum_{j=1}^m w^j / a_{it}^{jN}$. The firm then defines the new vector of input productivities $(a_{i(t+1)}^1; \ldots; a_{i(t+1)}^j; \ldots; a_{i(t+1)}^m)$ for the next period.

3.3. *R&D effort for the next period*

Having selected the technique to use in the next period, firms have then to decide on the R&D investment for the next period. This is modelled in two stages. As a first step, firms determine whether they want to adjust its level of R&D investment towards the industry average. This decision is made by comparing the performance (i.e. the present value of expected profits) of each firm and the industry average. A firm will decide to increment the R&D expenditures if its net present value is lower than the industry average, that is, if $V_{it} > V_t$. We assume that expected profits are determined by current and past profits. As a consequence, firms in the neighbourhood of the technology frontier exhibit higher net present value than those further behind the technological boundary. Formally, the net present value of an established firm with an infinite horizon and a constant discount rate (ν) is given by:

$$V_{it} = \pi_{it} + \sum_{\tau=t+1}^{\infty} (1+\nu)^{-\tau} E(\pi_{i\tau}), \tag{15}$$

where $E(\pi_{i\tau})$ is the expected profit in period t. $E(\pi_{i\tau}) = (1+\hat{g}_{it}^\pi)\hat{\pi}_{it}$, where $\hat{\pi}_{it} = \rho\hat{\pi}_{i(t-1)} + (1-\rho)\pi_{it}$ and $\hat{g}_{it}^\pi$ is the average profit growth rate given by $\hat{g}_{it}^\pi = \varphi\hat{g}_{i(t-1)}^\pi + (1-\varphi)g_{it}^\pi$, if $\hat{g}_{it}^\pi > 0$, or $\hat{g}_{it}^\pi = 0$ otherwise. φ and ρ are weighting parameters, with $\varphi, \rho \in [0,1]$.

Eq. (15) can then be written:

$$\begin{cases} V_{it} = \pi_{it} + \dfrac{\hat{\pi}_{it}}{\nu - \hat{g}_{it}^\pi}, & \text{for} \quad \hat{g}_{it}^\pi < \nu, \\ V_{it} = +\infty, & \text{for} \quad \hat{g}_{it}^\pi \geq \nu \quad \text{and} \quad \hat{\pi}_{it} > 0, \\ V_{it} = -\infty, & \text{for} \quad \hat{g}_{it}^\pi \geq \nu \quad \text{and} \quad \hat{\pi}_{it} < 0, \\ V_{it} = \pi_{it}, & \text{for} \quad \hat{\pi}_{it} = 0. \end{cases} \tag{16}$$

The average net present value of the industry is given by:

$$\bar{V}_t = \sum_{\tau=t}^{\infty} (1+\nu)^{-\tau} E(\pi_\tau) \quad \text{or} \quad \bar{V}_t = \hat{\pi}_t \left(1 + \frac{1}{\nu}\right), \tag{17}$$

assuming $E(\pi_\tau) = \hat{\pi}_t$; with $\hat{\pi}_t = \psi\hat{\pi}_{(t-1)} + (1-\psi)\bar{\pi}_{t-1}$. ψ is the weighting parameter ($0 < \psi < 1$) and $\bar{\pi}_t = \sum_{i=1}^{n_t} s_{it}\pi_{it}$.

Thus, the desired R&D investment rate for the next period, $r_{i(t+1)}^{des}$, is determined according to the following rule:

$$\begin{cases} \text{If} \quad V_{it} \geq \bar{V}_t, & r_{i(t+1)}^{des} = r_{it}, \\ \text{If} \quad V_{it} < \bar{V}_t, & r_{i(t+1)}^{des} = (1-\beta_i)r_{it} + \beta_i \bar{r}_{(t-1)} + \omega_{it}, \end{cases} \tag{18}$$

where $\bar{r}_{(t-1)}$ is the weighted average R&D expenditure rate in period $t-1$ ($\bar{r}_t = \sum_{i=1}^{n_t} s_{it} r_{it}$), β_i is the firm-specific parameter that gives the rate of adjustment ($0 < \beta_i < 1$), and ω_{it} is a random variable. According to this rule, if a firm's performance is not satisfactory (i.e. if it is less technologically advanced), the R&D effort will increase in the direction of the industry R&D average.

Finally, the R&D expenditure rate to be implemented by the firm in the following periods is determined. It is assumed that the rate of R&D investment is bounded from above by the unit profit before non-production costs, such that the R&D expenditure rate in the next period is given by:

$$r_{i(t+1)} = \min \left[r_{i(t+1)}^{des}, \max \left(1 - \frac{c_{it}}{P_t}, 0 \right) \right], \tag{19}$$

that is, if the price-cost margin is negative, the firm does not invest in R&D.

3.4. Entry and exit

In each period, firms decide whether to continue or exit and potential entrants decide whether to enter or not. We assume that entry and exit barriers are connected to the structural characteristics of the industry (i.e. the technological regime), given by entry and exit costs, E and X, respectively. (These costs, however, are never set to preclude entry or exit of firms.) The entry barriers are determined by the nature of the knowledge base and by the properties of the learning processes (Marsili, 2001). Exit barriers influence the behaviour of firms by imposing non-transferability of specific assets, such as specific skills and accumulated knowledge (Caves and Porter, 1976), and therefore they are expected to be higher in the routinized regime.

The exit decision is taken in period t, and it is implemented at the beginning of period $t+1$. A firm will decide to stay in the industry if $V_{it} \geq V_{it}^X$, that is, if the corresponding net present value is higher than the alternative (exit). V_{it}^X is the net present value of an established firm that decides to exit and it is given by:

$$V_{it}^X = \pi_{it} - X. \tag{20}$$

Considering (15) and (20), a firm decides to stay if positive profits are expected or if the absolute value of expected losses is lower than the exit cost, yielding the following rule:

$$\begin{cases} \text{Stay}, & \text{if} \quad E(\pi_{it}) > 0 \\ \text{Stay}, & \text{if} \quad E(\pi_{it}) < 0 \text{ and } \left| \sum_{\tau=t+1}^{+\infty} (1+\nu)^{-\tau} E(\pi_{it}) \right| \leq X \\ \text{Exit}, & \text{otherwise}. \end{cases} \tag{21}$$

Note that a given firm decides to operate with negative profits if and only if the corresponding losses are lower than the cost of the non-transferable (specific) assets. Given that we do not assume any financial mechanism to cover losses, this hypothesis is equivalent to consider that owners accept the no remuneration case of specific assets in the case of exit (that will loss anyway if the firm exit the market).

Based on condition (16), the rule in (21) can be then written as:

$$\begin{cases} \text{Stay}, & \text{if} \quad \hat{\pi}_{it} \geq 0 \\ \text{Stay}, & \text{if} \quad \hat{\pi}_{it} < 0 \text{ and } \hat{g}_{it}^{\pi} < \nu \text{ and } \left| \hat{\pi}_{it} \right| \leq (\nu - \hat{g}_{it}^{\pi})X \\ \text{Exit}, & \text{otherwise}. \end{cases} \tag{22}$$

Entry varies according to the technological regime. In the entrepreneurial regime, the innovative draws are linked to a universal 'science-based' knowledge. Thus, the innovative entry is easy and diversified in their form, via, for example, spin-offs generated by research institutions. Typically, a highly cumulative knowledge, low knowledge spillover across firms and low learning from public sources, as in routinized regime, results in higher technological entry barriers. In this case, large technology-based firms encompass several technologies with a potential for innovation in other business areas outside their own area. As large firms commonly do not spur such opportunities spin-offs may take advantage of this neglected potential, representing the main form of entry (Dahlstrand, 1997).[12]

Formally, the number of entrants can be defined in several ways. For example, Llerena and Oltra (2002) and Winter (1984) define the number of potential entrants as a stochastic Poisson process to then evaluate whether potential entrants become actual entrants, while Marsili (2001) defines the number of entrants exogenously, using a constant entry rate with a stochastic disturbance. Our implementation is similar to the latter. Thus, we define the number of new firms as follows:

$$m_t = \gamma_t n_{t-1}, \tag{23}$$

where m_t is the number of entrants in period t (approximated at the nearest integer), γ_t ($\gamma_t > 0$) is the entry rate and n_{t-1} is the number of established firms in the period $t-1$. The entry rate is given by a normal distribution $\gamma_t \sim N(\mu_E, \sigma_E^2)$, with $\mu_E = f(E)$ and $f' < 0$ (i.e. γ_t is decreasing with the level of entry barriers, which are lower in the entrepreneurial regime than in the routinized regime).

The entry decision is taken in period t and becomes effective at the beginning of period $t+1$. In the entrepreneurial regime, the improvements in the current state of technological knowledge are mainly due to the new firms, while in the routinized regime such improvements are mostly associated to the established ones. The productivity level of inputs of new firms are thus drawn from a log normal distribution centred on the log of industry average productivity (i.e. the representative incumbent firm; $\mu_{et}^j = \ln \bar{a}_{t-1}^j$) in the routinized regime,

[12] Using the data from 60 small Swedish technology-based firms, Dahlstrand (1997) found that as many as two-thirds of all spin-offs were originated in private firms, and just one-sixth from universities. However, whether the effects of spin-off formation are more likely in the one or in the other technological regime is still unclear (Buerger et al., forthcoming).

and on the log of best practice observed in the industry (i.e. the technological frontier; $\mu_{et}^{j} = \ln[(1+g_{et}^{j})\tilde{a}_{t-1}^{jM}]$) in the entrepreneurial regime ($\tilde{a}_t^{jM}$ is given by Eq. (13) above; subscript e denotes potential entrant). That is, in the former case the technology of new firms is mainly related with established firms, while in the latter it is linked with a broad and universal knowledge based in the science.

Whether a *potential entrant* becomes an actual *entrant* depends on the evaluation of the profit opportunities generated by its technology at the time of entry. The potential entrants can be mistaken about the evaluation of the profit opportunity via, namely, a bad judgement of the potential productivity level of the technique. The net present value of a potential entrant is given by:

$$V_{et}^{E} = \sum_{\tau=t+1}^{\infty} (1+\nu)^{-\tau} E(\pi_{i\tau}) - E. \tag{24}$$

A potential entrant decides to enter the industry if the (discounted) expected profits are higher than the entry cost, that is, if

$$E(\pi_{et}) > \nu E. \tag{25}$$

The production technique is defined at the outset in case of entry. The full specification of the initial characteristics of each firm is therefore required. We assume, in particular, that the entry scale is small relative to the size of the market and determined by a normal distribution $q_{et} \sim N(\mu_q, \sigma_q^2)$, with $\mu_q < \bar{q}_t$. Whether the R&D effort is innovative or imitative is randomly determined. The remaining parameters are similar to those for the established firms.

4. Some analytical properties of the model: no learning case

Before tackling the full-fledged version of the model in Section 5, let us begin by studying some analytical properties of the special case of an *industry with no learning*. Firstly, let us assume that *all* firms share the same technology and level of knowledge—that is, $(a_{it}^1; \ldots; a_{it}^m) = (a_{nt}^1; \ldots; a_{nt}^m)$ and $u_{it} = u_{nt}$, for all i, $n \in I$ —which implies that individual firms' production level is constant over time and equal to $\bar{q}$. This is indeed the closest formulation of the static classical model of a competitive industry. In this scenario, it is realistic to assume that expected profit is equal to the current profit, and so the exit condition (22) can be rewritten as $D/n_t - c\bar{q} + \nu X < 0$, while the entry condition (25) is given by $D/n_t - c\bar{q} - \nu E > 0$.[13] Thus, the market price and the number of firms is given by $c - (\nu X/\bar{q}) \leq P_t \leq c + (\nu E/\bar{q})$ and $D/(c\bar{q} + \nu E) \leq n_t \leq D/(c\bar{q} - \nu X)$, respectively. Obviously, in this case, there is no industry productivity growth. If entry and exit barriers are zero, the equilibrium is given by price equal to marginal cost ($P_t = c$).

Let us now consider that firms are technologically heterogeneous. According to the replicator dynamic in Eq. (2), in each period, high-productivity firms (i.e. firms with a higher productivity than the weighted industry average) will gain market share, while the low-productivity firms will shrink. Then, as $t \to \infty$, and given that $\bar{c}_t = \sum_{i=1}^{n_t} s_{it} c_{it}$, $\bar{c}_t$ converges towards the lowest unit production cost, $\tilde{c}$, the market will be eventually dominated by the highest-productivity firm.[14]

This scenario changes after introducing entry and exit, with results depending on whether new firms can adopt the best technique, as in entrepreneurial regime, or not, as in routinized regime. In the latter, we end up with a monopoly, with production, q_{nt}, given by $(D - \nu E)/\tilde{c} \leq q_{nt} \leq (D + \nu X)/\tilde{c}$. Even if each individual productivity level is fixed, the industry productivity level increases up to the point where $\bar{c}_t = \tilde{c}$.[15] In the entrepreneurial regime case, if one admits that new high-productivity firms enter with certain regularity, new and old firms/techniques will compete against each other and the market will not converge towards a monopoly. The selection mechanism in turn will systematically exclude from the market low-productivity firms and, as a consequence, the industry productivity level will rise.

5. Numerical analysis: the impact of entry and exit on industry productivity growth

More than testing fully the sensitivity of the results to parameter perturbation or assessing universal properties of the model—tasks unfeasible given the complexity of the model and the number of parameters involved—the main purpose of our numerical simulation is just to shed further light on the routes through which entry is able to generate industry productivity growth.[16] To begin with, however, we evaluate to what extent the model is able to replicate some of the stylized empirical regularities on firm dynamics reported in Section 2.[17]

In each technological regime, we consider five separate entry/exit scenarios of 200 consecutive production periods (quarters). To test for the robustness of our findings with respect to model parameterization (the model assumes a considerable number of random parameters), each scenario is replicated 100 times, making a total of 100 × 200 runs per scenario. Either the number of production periods or the number of replications could be easily extended, but no substantial gain would be obtained. We believe indeed to have generated sufficiently and representative statistics that allows us to establish our findings with a comfortable degree of confidence.

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[13] Given that the technology exhibits constant returns to scale, using (7) we have $\pi_{it} = D/n_t - c\bar{q}$.

[14] The speed of convergence to a monopoly depends on δ. If $\delta = 1$, 0.5 and 0.1, then the industry becomes a monopoly after, respectively, 3548, 7095 and 34,471 periods.

[15] Defining the industry aggregate productivity, A_t as the weighted average of firms' productivity (that is, $A_t = \sum_{i=1}^{n_t} s_{it} a_{it}$, where a_{it} is the productivity index of firm i), the market share of low- (high-) productivity decreases (increases) as t increases. In the limit, A_t converges towards the highest firm's productivity level, $\tilde{a}$.

[16] See, for example, Brenner and Werker (2007) and Marengo and Valente (2010) for a discussion about the goal of the simulation exercises.

[17] The numerical simulation was implemented by using the *Laboratory for Simulation Development* software, a free simulation package developed by Valente (2008). The software is available for downloading at http://www.labsimdev.org. The corresponding code and configuration files are available from the authors upon request.

Table 1
Selected industry statistics.

	No entry–no exit	Routinized regime					Entrepreneurial regime				
		Entry parameters									
		0.01050	0.01075	0.01100	0.01125	0.01150	0.03800	0.03825	0.03850	0.03875	0.03900
Average over 200 periods											
Number of firms	65.00	111.42	111.45	111.43	111.46	111.48	127.35	123.74	126.15	128.32	126.16
		(9.098)	(9.125)	(9.136)	(9.188)	(9.165)	(30.461)	(23.469)	(28.159)	(48.271)	(29.926)
Herfindahl index (inverse)	55.65	105.79	105.84	105.80	105.82	105.82	120.39	117.60	119.84	121.48	119.99
	(3.329)	(7.425)	(7.472)	(7.461)	(7.496)	(7.495)	(24.116)	(19.755)	(25.068)	(45.146)	(26.163)
Hymer–Pashingian index	0.008	0.024	0.024	0.024	0.024	0.024	0.031	0.031	0.032	0.032	0.032
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.030)	(0.026)	(0.027)	(0.026)	(0.027)
Entry rate (per quarter)	–	0.018	0.018	0.018	0.019	0.019	0.046	0.047	0.047	0.047	0.047
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.009)	(0.007)	(0.005)
Exit rate (per quarter)	–	0.007	0.007	0.007	0.007	0.008	0.035	0.036	0.036	0.036	0.036
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.042)	(0.040)	(0.039)	(0.040)	(0.041)
Final period ($t = 200$)											
Number of firms	65.00	123.57	123.18	123.54	123.68	123.39	147.47	135.76	144.15	163.03	143.84
		(3.723)	(3.888)	(4.580)	(4.895)	(4.880)	(61.691)	(35.395)	(41.729)	(108.632)	(55.700)
Herfindahl index (inverse)	51.84	114.39	114.02	114.13	114.15	113.74	126.46	119.65	122.32	138.85	124.45
	(1.79)	(3.749)	(3.525)	(4.148)	(4.354)	(4.755)	(40.064)	(32.587)	(32.517)	(101.369)	(34.251)
Hymer–Pashingian index	0.005	0.022	0.022	0.022	0.022	0.023	0.036	0.042	0.030	0.032	0.035
	(0.003)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.062)	(0.088)	(0.017)	(0.049)	(0.053)
Entry rate (per quarter)	–	0.017	0.017	0.017	0.018	0.018	0.046	0.046	0.046	0.047	0.047
		(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)	(0.009)	(0.007)	(0.005)
Exit rate (per quarter)	–	0.008	0.008	0.008	0.008	0.009	0.040	0.035	0.029	0.038	0.042
		(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.083)	(0.075)	(0.021)	(0.070)	(0.072)

Notes: Average over 100 simulation runs for each industry configuration. Standard deviations are in parentheses.

To begin with, we have the no entry/no exit case as a benchmark. Then, using the entry rates reported in Dunne et al. (1988) and Audretsch and Acs (1994), we calibrate the mean of the random entry rate (i.e. μ_E of γ_t) to 1.050, 1.075, 1.100, 1.125 and 1.150% per quarter in the corresponding five routinized regime cases, and 3.800, 3.825, 3.850, 3.875 and 3.900% per quarter in the other five entrepreneurial regime cases. The parameter defining exit barriers is assumed to be equal to 2 in the routinized regime (high barriers) and 0 in the entrepreneurial regime (low barriers).

All other industry and firm parameters are identical across implementations. In particular, our exercise considers an initial population of 65 heterogeneous/single-output/single establishment firms with distinct R&D intensity and productivity levels. To simplify, the production technology uses only two inputs, with the initial productivity level of input 1 ranging from 0.868 to 1.101, and from 1.536 to 1.745 in the case of input 2. The corresponding averages are equal to 0.999 and 1.643. The initial R&D rate per unit of sales ranges between 0.5 and 9.0%, with an average equal to 4.77%. The average initial market share is identical for all firms and equal to 0.0154 (or 1/65). As in the Nelson–Winter model, we assumed a 'mature' market with a unit elastic (inverse) demand given by $P_t = 65/Q^D$. The values of parameters are presented in Appendix A.

Other simulation exercises were carried out using different learning parameters, but no material changes were detected with exception of the productivity growth rate which seems slightly sensitive to parameter perturbation. In the text below, we only report the results from simulations directly linked to the main goal of our exercise, that is, those connected with the relationship between firm dynamics (namely entry and exit) and aggregate productivity growth.

5.1. Analysing the evolution of industry

So how does the model fare in terms of its ability to replicate the empirical regularities on firm dynamics documented in Section 2? Table 1 shows the selected industry statistics generated by each industry configuration. Clearly, the final number of firms is (11–15%) higher in the entrepreneurial regime than in the routinized regime, either in terms of the average over the entire production cycle (200 periods) or at the final period (i.e. at $t = 200$). The Herfindahl–Hirschman equivalent number of firms index shows in turn that market concentration is

Table 2
Annual entry and exit rates.

	Routinized regime					Entrepreneurial regime				
	Entry parameters									
	0.01050	0.01075	0.01100	0.01125	0.01150	0.03800	0.03825	0.03850	0.03875	0.03900
Average over 50 years										
Entry rate	0.0288	0.0290	0.0294	0.0298	0.0303	0.1340	0.1339	0.1353	0.1360	0.1369
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.020)	(0.019)	(0.024)	(0.019)	(0.017)
Exit rate	0.0173	0.0176	0.0179	0.0182	0.0188	0.1174	0.1199	0.1200	0.1197	0.1216
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.072)	(0.066)	(0.066)	(0.066)	(0.068)
Final period										
Entry rate	0.0233	0.0236	0.0259	0.0274	0.0288	0.1341	0.1343	0.1367	0.1388	0.1396
	(0.007)	(0.008)	(0.010)	(0.009)	(0.010)	(0.028)	(0.024)	(0.028)	(0.024)	(0.023)
Exit rate	0.0202	0.0203	0.0205	0.0231	0.0258	0.1270	0.1270	0.1324	0.1283	0.1238
	(0.012)	(0.014)	(0.014)	(0.014)	(0.016)	(0.160)	(0.119)	(0.133)	(0.121)	(0.130)

Notes: Averages over 100 simulation runs for each industry configuration. The rates are defined as the ratio of entrants (exiting firms) in t to the total number of firms in $t-1$. Standard deviations are in parentheses.

Table 3
Survival rate of new firms (in percentage).

		Years after birth									
		1 year	2 years	3 years	4 years	5 years	6 years	7 years	8 years	9 years	10 years
Routinized regime											
Entry parameter	0.01050	86.4	83.1	80.1	77.1	74.1	71.4	68.6	65.8	63.3	60.7
	0.01075	86.7	83.4	80.2	77.2	74.2	71.4	68.6	65.7	63.1	60.5
	0.01100	86.5	83.1	80.0	76.8	73.9	70.8	68.1	65.1	62.5	59.9
	0.01125	86.3	82.8	79.4	76.2	73.3	70.4	67.7	64.9	62.3	59.7
	0.01150	86.4	82.8	79.3	76.0	72.8	70.0	67.3	64.3	61.7	59.1
Entrepreneurial regime											
Entry parameter	0.03800	83.5	70.6	59.6	50.5	43.1	36.7	31.5	27.1	23.4	20.4
	0.03825	83.5	70.5	59.5	50.3	42.8	36.4	31.3	26.9	23.3	20.2
	0.03850	83.0	70.2	59.4	50.2	42.6	36.2	31.0	26.7	23.0	19.9
	0.03875	83.4	70.4	59.2	50.0	42.3	36.1	30.8	26.5	22.9	19.8
	0.03900	83.5	70.3	59.2	49.8	42.2	35.7	30.5	26.2	22.5	19.4

Notes: Averages over 100 simulation runs for each industry configuration. The survival rate is defined as the number of new firms surviving in a given year after birth, as a percentage of the total number of new firms.

higher in the routinesed regime than in the entrepreneurial regime.[18] At $t=200$, for example, there are between 113.7 and 114.4 'equivalent' firms in the routinized regime, and 119.7–138.9 in the entrepreneurial regime. The corresponding standard deviations are also considerably higher in the latter.

Comparing with no entry/no exit scenario, all 10 selected scenarios generate larger rates of turbulence. As shown by the Hymer–Pashingian index (line 3, panels (a) and (b), columns 3 and 8), 3.2% of the total market share, on average, are transferred across firms in the entrepreneurial regime, while in the routinized regime this figure is only 2.4%.[19] There is, therefore, one third more turbulence in the entrepreneurial regime than in the routinized regime, a pattern very close to the one found by Audretsch and Acs (1990). In the no entry/no exit scenario, this reallocation rate does not exceed 0.8%. Thus, most of this reallocation is mainly caused by the competitive pressure of new firms.

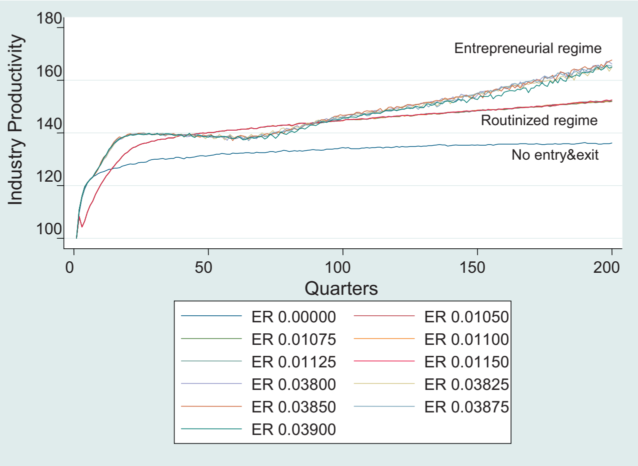
Much of the market turbulence is of course linked to the entry and exit of firms. As Table 2 shows, the annual entry and exit rates are quite distinct in the two technological regimes.[20] For example, the entrepreneurial regime yields an annual entry rate of 13.5% and an exit rate of 12.0% (averages over the 200 periods), while for the routinized regime the corresponding entry and exit rates are 2.9% and 1.8%. This finding confirms some stylised facts, according to which many industries, especially those closer to the routinized regime, show average annual entry rates lower than 3%, while other industries, closer to the entrepreneurial regime, exhibit entry rates higher than 12% (Dunne et al., 1988; Geroski, 1991; Baldwin, 1995).

Entry and exit are highly positively correlated. This correlation is determined, in the first instance, by the rate of early mortality of new firms, which is very high in both technological regimes. Table 3 provides the distribution of the number of production periods in which newly created firms operate before closing. Around 14% of new firms

18 The Herfindahl–Hirschman index, HH_t, is an indicator of market concentration and is given by $HH_t = \sum_{i=1}^{n_t} s_{it}^2$, with s_{it} denoting the market share of firm i.

19 The Hymer–Pashingian instability index, I_t, is an indicator of market turbulence, and it is computed as the sum of one-period variations in absolute value in firms' market shares: $HP_t = \sum_{i=1}^{n_t} \left| s_{it} - s_{i(t-1)} \right|$ or $HP_t = \sum_{c=1}^{c_t} \left| s_{ct} - s_{c(t-1)} \right| + \sum_{e=1}^{e_t} s_{et} - \sum_{x=1}^{x_t} s_{x(t-1)}$, where c denotes continuing firms, e new firms, and x exiting firms.

20 Entry and exit rates, ER_{it} and XR_{it}, are computed using the method suggested by Dunne et al. (1988).



Notes: Base 100 at *t=0*. ER 0.00000-ER 0.03875 denote the industry productivity index associated with the corresponding mean of the random entry rate.

Fig. 2. Industry productivity. *Notes*: Base 100 at $t=0$. ER 0.00000–ER 0.03875 denote the industry productivity index associated with the corresponding mean of the random entry rate.

close within the first year (i.e. before four production periods) in the routinized regime, while in the entrepreneurial regime the corresponding figure is approximately 17%. Ten years after birth, 60% of entrants are still in operation in the routinized regime. The corresponding rate in the entrepreneurial regime is only 20%, which has a higher entry rate too. This of course confirms the stylised fact that early mortality among entrants is particularly high in the entrepreneurial regime, as found by Geroski (1991), Audretsch (1991), Mata et al. (1995) and Baldwin (1995).

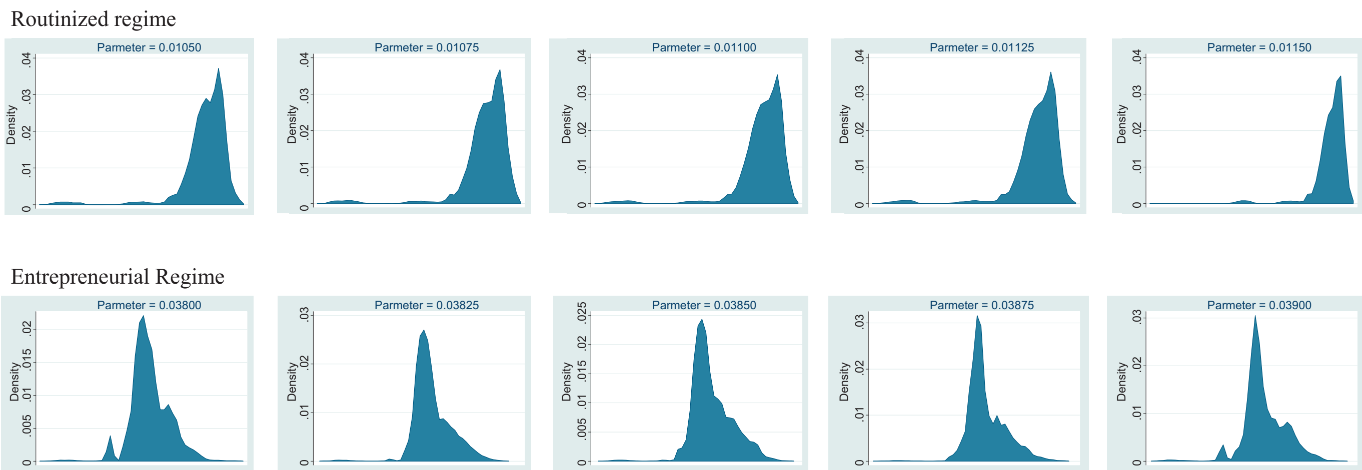
5.2. Firm dynamics and industry-level productivity growth

The next issue is whether all the generated firm mobility implies a higher aggregate productivity growth. Let us first compare the productivity growth across the two technological regimes. Fig. 2 plots the evolution of aggregate productivity. (Individual productivity levels are weighted by the corresponding market shares.) Both technological regimes generate a higher Fisher index of productivity than in no entry/no exit scenario: the final period productivity index is, respectively, 167.6 and 152.5 in the entrepreneurial and routinized regimes, and only 136.3 in the case of no entry/no exit (base 100 at $t=0$). Converting into annual average growth rates, this is equivalent to 1.04, 0.85, and 0.62%, respectively.

As Fig. 3 and Table 4 show the 'technological space' is exploited differently across the two types of technological regimes. In the first place, dispersion in productivity levels is higher in the entrepreneurial regime than in the routinezed regime. (The lowest dispersion is in the no entry/no exit scenario.) The productivity distribution is left-skewed in the case of routinized regime, with a long tail in the negative direction (i.e. the mean is lower than the median–the negative skewness is indeed between −3.48 and −3.26). In the entrepreneurial regime, in contrast, the distributions are weakly right-skewed. The maximum productivity level in the routinized regime is also much closer to the third quantile than in the entrepreneurial regime case. Thus, the more concentrated productivity distribution on top values in the former case does not result in a higher average productivity growth rate.

Successful firms exclude unsuccessful ones and the result is a considerable resource reallocation and, hopefully, increased aggregate productivity growth. As Table 5 shows, the market share transferred from exiting and contracting units to entering and expanding units, over a 5-year period, was 12–13% in the routinized regime. The corresponding rate in the entrepreneurial regime is an astonishing 51–52%, while in the no entry/no exit scenario, the market share reallocation is very small at 5%. Therefore, the increase in the competitive pressure through entry leads to a higher level of market share reallocation. To evaluate whether this reallocation generates an aggregate productivity gain, we next investigate which firms gain/lose market share.

In order to disaggregate the contribution of firm dynamics to industry productivity growth, the population of firms in each 5-year period was divided into four groups: con-



Note: Pooling of 100 simulations (final period).

Fig. 3. Distribution of the final period productivity of firms. *Note*: Pooling of 100 simulations (final period).

Table 4
Distribution of the final period productivity of firms.

	No entry–no exit	Routinized regime					Entrepreneurial regime				
		Entry parameters									
		0.01050	0.01075	0.01100	0.01125	0.01150	0.03800	0.03825	0.03850	0.03875	0.03900
Average	202.79	227.61	227.64	228.12	228.04	228.15	242.58	241.20	244.09	239.94	240.42
Standard deviation	15.95	19.70	19.93	19.52	19.83	19.86	26.09	23.35	25.25	23.91	25.96
Minimum	80.96	96.15	96.52	95.66	96.74	98.46	98.82	105.54	107.32	103.66	104.40
First quantile	204.98	221.99	221.97	222.07	222.07	222.17	227.59	226.54	227.29	225.58	227.02
Median	206.84	230.93	231.18	231.50	231.73	232.33	238.97	235.80	237.80	233.02	234.73
Third quantile	207.88	238.87	238.91	239.93	239.71	239.68	257.32	253.50	258.26	252.55	254.92
Maximum	211.97	257.12	254.07	255.20	257.69	255.11	363.53	332.92	341.60	339.05	340.01

Note: Pooling of 100 simulations (final period).

Table 5
Net market share transferred from closings and contractions to openings and expansions, over 5-year period (in percentage).

	No entry–no exit	Routinized regime					Entrepreneurial regime				
		Entry parameters									
		0.01050	0.01075	0.01100	0.01125	0.01150	0.03800	0.03825	0.03850	0.03875	0.03900
Average of 5-year periods	4.91	12.49	12.63	12.80	12.98	13.28	50.71	51.02	51.15	51.21	52.15
	(1.20)	(2.03)	(2.05)	(2.04)	(2.04)	(2.08)	(6.12)	(5.93)	(6.43)	(6.08)	(6.31)

Notes: Averages over nine 5-year periods and 100 simulation runs for each industry configuration. Standard deviations are in parentheses.

tinuing firms with increasing market shares, continuing firms with decreasing market shares, exiting firms, and entering firms. In each group we then computed the proportion of firms with a productivity index higher than the average/median productivity of continuing firms. For completeness, the productivity of entering firms was also compared with the productivity of exiting firms. These statistics are presented in Tables 6 and 7. The reported values are the averages over a time-span of 9 consecutive 5-year periods (i.e. over a total of 180 runs in each of 100 replications; the first 5-year period was dropped from the analysis).

Table 6
Proportion of entrants (exits) with higher (lower) productivity than average/median productivity of continuing firms (in percentage).

	Routinized regime					Entrepreneurial regime				
	Entry parameters									
	0.01050	0.01075	0.01100	0.01125	0.01150	0.03800	0.03825	0.03850	0.03875	0.03900
New firms with a productivity index higher than:										
Continuing firms' average	66.87	66.99	66.95	67.72	68.12	47.22	47.03	47.33	47.07	48.53
	(14.57)	(14.90)	(15.34)	(15.31)	(15.36)	(39.89)	(39.00)	(39.55)	(39.72)	(40.25)
Continuing firms' median	40.70	41.02	41.13	42.32	43.34	60.87	58.58	59.41	61.09	62.89
	(21.31)	(21.60)	(21.27)	(21.41)	(21.18)	(37.54)	(37.90)	(37.80)	(37.56)	(37.09)
Exiting firms' average	47.47	48.01	47.71	50.15	49.90	75.30	75.58	72.97	74.75	76.15
	(28.42)	(28.28)	(28.52)	(27.87)	(27.10)	(32.60)	(32.11)	(33.36)	(32.37)	(31.73)
Exiting firms with a productivity index lower than:										
Continuing firms' average	67.91	67.45	68.39	67.97	68.75	92.93	93.12	93.01	93.12	93.22
	(18.69)	(18.81)	(18.07)	(18.30)	(18.07)	(5.11)	(4.90)	(5.24	5.06)	5.07)
Continuing firms' median	74.96	74.98	74.98	74.95	75.69	93.12	93.28	93.26	93.25	93.44
	(17.09)	17.73)	(16.85)	(17.51)	(16.72)	(4.81)	(4.71)	(4.93)	(4.85)	(4.82)

Notes: Averages over nine 5-year periods and 100 simulation runs for each industry configuration. The group of entering (exiting) firms comprises all firms that enter (exit) in a given period. Simultaneous entry and exit within any period is precluded. The reported values are obtained by dividing the number of entrants (exits) with a higher (lower) productivity index than the corresponding average of continuing firms by the total number of observed entrants (exits). The productivity index of continuing firms is measured at the beginning-period in the case of new firms and at the ending-period in the case of exits. Standard deviations are in parentheses.

Table 7
Proportion of continuing firms with increasing (decreasing) market shares with higher (lower) productivity than average and median productivity of whole continuing firms group (in percentage).

	Routinized regime					Entrepreneurial regime				
	Entry parameters									
	0.01050	0.01075	0.01100	0.01125	0.01150	0.03800	0.03825	0.03850	0.03875	0.03900
Continuing firms with increasing market shares and productivity above:										
Continuing firms' average at $t-1$	97.10	97.06	96.95	97.01	97.02	83.99	83.93	83.08	82.96	81.79
	(6.44)	(6.44)	(6.80)	(6.77)	(7.68)	(24.82)	(24.52)	(25.03)	(25.80)	(26.96)
Continuing firms' average at t	87.60	87.82	87.64	87.99	88.37	85.03	84.71	83.24	83.03	83.29
	(13.22)	(13.18)	(13.30)	(13.08)	(13.23)	(21.48)	(21.73)	(22.92)	(23.57)	(23.59)
Continuing firms' median at $t-1$	83.68	83.63	83.42	83.58	83.37	80.42	80.19	79.58	80.23	77.71
	(14.34)	(14.36)	(14.64)	(14.82)	(14.98)	(27.13)	(27.23)	(27.21)	(27.32)	(29.26)
Continuing firms' median at t	60.41	60.32	59.94	59.92	59.93	76.30	76.27	76.20	76.00	73.77
	(18.38)	(18.51)	(18.85)	(19.05)	(18.75)	(27.95)	(28.16)	(28.01)	(27.99)	(29.43)
Continuing firms with decreasing market shares and productivity below:										
Continuing firms' average at $t-1$	39.10	38.99	38.60	38.42	38.14	54.01	54.68	55.61	54.01	54.01
	(18.00)	(18.04)	(17.83)	(17.63)	(17.72)	(33.15)	(33.44)	(33.88)	(33.12)	(34.06)
Continuing firms' average at t	52.89	52.82	52.47	52.38	52.36	68.26	68.73	69.50	68.88	67.56
	(14.31)	(14.30)	(14.18)	(14.25)	(14.35)	(24.01)	(24.48)	(24.13)	(23.99)	(25.11)
Continuing firms' median at $t-1$	52.47	52.32	51.85	51.85	51.79	46.62	48.24	48.02	46.98	48.16
	(15.89)	(15.88)	(15.56)	(15.59)	(15.64)	(29.18)	(29.40)	(29.98)	(29.82)	(29.37)
Continuing firms' median at t	59.45	59.35	58.94	58.98	58.96	60.77	62.91	62.82	60.98	61.69
	(11.13)	(11.09)	(10.87)	(11.00)	(10.86)	(24.77)	(24.18)	(24.56)	(25.62)	(24.57)

Notes: Averages over nine 5-year periods and 100 simulation runs for each industry configuration. The group of continuing firms comprises all firms that remain active over a given period. In this group, firms were divided into two categories: those with an increasing market share and those with a decreasing market share. The proportions reported in the table for each group are then obtained dividing the number of firms with a higher productivity level than the average of continuing firms by the total number of observed firms in the corresponding category. Standard deviations are in parentheses.

Table 6 shows that entrants are at least as productive as continuing firms. In the routinized regime, 67–68% of entrants show a productivity-level above the (beginning-period) average of continuing firms (line 1, columns 1–5). In the case of the entrepreneurial regime, only roughly one half of entering firms are more productive than the continuing firms average (line 1, columns 6–10), but they are clearly more productive than the average of exiting firms (measured at the beginning-period) and the median of continuing firms (lines 2 and 3, columns 6–10). That is, the gains in the aggregate productivity through entry are not mostly due to entry of higher productivity firms, but rather to the fact that firms force the least productive ones to exit.

The exiting firms are also strongly concentrated in the less productive lot in both technological regimes. In the routinized regime, 67–69% of exiting firms have a productivity level below the (ending-period) average of continuing firms; approximately 75% are below the median. These proportions are larger in the entrepreneurial regime: approximately 93% in both cases. On the whole there is therefore no shadow of doubt that exits have been replaced by new and more productive firms, especially in the entrepreneurial regime case.

Table 7 looks at *continuing firms with increasing/decreasing market shares* in detail. At first sight it seems that most firms which are gaining market share are also more productive. In the routinized regime, for example, 83–84% of firms with increasing market shares belong to the (beginning-period) top 50% most productive continuing firms (line 3, columns 1–5), while approximately 97% of those firms have a productivity level above the continuing firms average (lines 1, columns 1–5). The percentage is even higher in the entrepreneurial regime case, at 78–82% and 82–84%, respectively (lines 3 and 1, columns 5–10). Symmetrically, continuing firms with decreasing market shares are in general less productive. In the case of the routinized regime, for example, approximately 59% of firms that are losing market share are located in (ending-period) 50% less productive segment, while in the entrepreneurial regime this proportion is 61–63%. It is therefore quite clear that

Table 8
Productivity growth decomposition.

	Routinized regime					Entrepreneurial regime				
	Entry parameters									
	0.01050	0.01075	0.01100	0.01125	0.01150	0.03800	0.03825	0.03850	0.03875	0.03900
Productivity growth	0.0101	0.0102	0.0104	0.0105	0.0104	0.0237	0.0223	0.0229	0.0214	0.0233
	(0.0219)	(0.0229)	(0.0253)	(0.0274)	(0.0294)	(0.0704)	(0.0650)	(0.0845)	(0.0635)	(0.0609)
Within	0.0253	0.0253	0.0256	0.0256	0.0257	0.0239	0.0233	0.0238	0.0232	0.0219
	(0.0230)	(0.0230)	(0.0229)	(0.0230)	(0.0235)	(0.0300)	(0.0312)	(0.0302)	(0.0300)	(0.0330)
Covariance	−0.0008	−0.0008	−0.0008	−0.0009	−0.0009	0.0028	0.0025	0.0028	0.0028	0.0022
	(0.0034)	(0.0033)	(0.0033)	(0.0033)	(0.0034)	(0.0070)	(0.0082)	(0.0068)	(0.0067)	(0.0094)
Entry	−0.0068	−0.0067	−0.0068	−0.0068	−0.0067	−0.0094	−0.0098	−0.0096	−0.0100	−0.0081
	(0.0042)	(0.0043)	(0.0042)	(0.0043)	(0.0045)	(0.0141)	(0.0139)	(0.0137)	(0.0145)	(0.0142)
Exit	−0.0004	−0.0004	−0.0004	−0.0003	−0.0005	0.0079	0.0081	0.0077	0.0078	0.0073
	(0.0028)	(0.0028)	(0.0028)	(0.0029)	(0.0029)	(0.0119)	(0.0118)	(0.0115)	(0.0114)	(0.0117)

Notes: Averages over nine 5-year periods and 100 simulation runs for each industry configuration. Dynamic Olley–Pakes decomposition (Melitz and Polanec, 2009). Standard deviations are in parentheses.

Table 9
Productivity growth regression, continuing firms.

	Routinized regime					Entrepreneurial regime				
	Entry parameters									
	0.01050	0.01075	0.01100	0.01125	0.01150	0.03800	0.03825	0.03850	0.03875	0.03900
Constant	0.4206**	0.4813**	0.4629**	0.4565**	0.4679**	0.1042**	0.1736**	0.0881**	0.1617**	0.1147**
	(0.0545)	(0.0525)	(0.0507)	(0.0508)	(0.0503)	(0.0143)	(0.0169)	(0.0130)	(0.0163)	(0.0139)
Entry rate	0.0636**	0.0608**	0.0607**	0.0620**	0.0661**	0.0527**	0.0528**	0.0482**	0.0549**	0.0459**
	(0.0037)	(0.0035)	(0.0033)	(0.0035)	(0.0033)	(0.0018)	(0.0020)	(0.0017)	(0.0019)	(0.0018)
Herfindahl-Hirschman Index	0.0710**	0.0844**	0.0803**	0.0779**	0.0806**	0.0112**	0.0259**	0.0084**	0.0232**	0.0148**
	(0.0122)	(0.0117)	(0.0112)	(0.0112)	(0.0109)	(0.0028)	(0.0034)	(0.0026)	(0.0033)	(0.0028)
Hymer–Pashingian index	−0.0516**	−0.0485**	−0.0479**	−0.0459**	−0.0531**	0.0120**	−0.0076*	0.0043	−0.0036	−0.0049
	(0.0062)	(0.0058)	(0.0055)	(0.0056)	(0.0052)	(0.0037)	(0.0038)	(0.0035)	(0.0038)	(0.0037)
Num. of observations	90,332	90,234	90,110	89,975	89,656	60,973	59,031	59,998	59,200	59,140
Wald test	686.00**	695.51**	693.05**	685.52**	722.09**	1029.24**	822.98**	1016.62**	987.08**	753.07**

Notes: Random-effects GLS regression of model (27). Pooling of 100 simulations runs for each industry configuration. Variables are in logarithmic form. Standard errors are given in parentheses. In all specifications, the Wald test rejects the null of no overall significance.
* Statistical significance at the .05 level.
** Statistical significance at the .01 level.

resource reallocation among continuing firms plays a substantial role on aggregate productivity growth, especially in the routinized regime case.

To evaluate the direct contribution of each group of firms to industry productivity growth between $t-\tau$ and t, we implemented the dynamic Olley–Pakes decomposition method suggested by Melitz and Polanec (2009):

$$\Delta A_t = \Delta\bar{A}_{Ct} + \Delta cov_{Ct}(\theta_{it}, a_{it}) + \theta_{Et}(A_{Et} - A_{Ct}) + \theta_{X(t-\tau)}(A_{C(t-\tau)} - A_{X(t-\tau)}), \quad (26)$$

where C, E, and X denote the group of continuing, entering, and exiting firms. θ_{gt} is the market share of group g in year t, A_{gt} is the weighted productivity average and $\bar{A}_{gt}$ is the unweighted productivity average ($g = C, E, X$). The first term on the right-hand-side of Eq. (26)—the 'within' term—captures the aggregate growth due to productivity changes in continuing firms. The 'covariance' term—the second term in (26)—gives the inter-firm resource reallocation towards more productive continuing firms. The last two terms capture the contribution of entering and exiting firms, respectively. The entry (exit) effect is positive if the productivity level of entering (exiting) firms is higher (smaller) than the productivity level of continuing firms in the corresponding year. The aggregate results are given in Table 8 and, clearly, the within effect is dominant. For its part, the entry effect is slightly negative in both technological regimes, while the exit effect is consistently positive and large in the entrepreneurial regime. What remains to be seen is the extent to which the within effect depends on firm entry intensity.

To this end, we use the following empirical model to evaluate whether firm entry has an impact on the productivity growth of continuing firms ($i \in C$):

$$\ln a_{ijt} = \beta_0 + \beta_1 \ln ER_{jt} + \beta_2 \ln HH_{jt} + \beta_3 \ln HP_{jt} + \eta_{ijt} \quad (27)$$

where η_{ijt} is a standard error term. The model was estimated using GLS random-effects. The variables are in logarithmic form so that the estimated coefficients can be read as elasticity parameters. As can be seen in Table 9, the coefficient of the entry rate variable is positively signed and statistically significant at conventional levels in all industry configurations. All else constant, if the entry rate increases by 1% then the productivity of continuing firms increases by 0.061–0.066% in the routinized regime and 0.046–0.055% in the entrepreneurial regime. In other words, the econometric results confirm the conjecture that entering firms do encourage continuing firms to improve their performance.

6. Concluding remarks

This paper examines industry dynamics as a source of industry productivity growth in two alternative technological regimes. It was assumed that new firms generate gains in the aggregate productivity through increased productivity and competitive pressure. Our evolutionary approach assumes that individual firms learn about technology through a variety of sources, and that, as a consequence, productivity growth and market shares across firms can be quite distinct. Aggregate productivity growth in this framework is thus determined by the micro productivity patterns associated with different technological regimes, on the one hand, and the ease of entry/exit, on the other.

Our numerical simulations do replicate key empirical regularities already reported in literature. In particular, they show that firm mobility has a strong impact on industry productivity growth: firms that gain market share are the ones among the most productive lot, while continuing firms with decreasing market shares are in the bottom half of the distribution in terms of efficiency; exiting firms also tend to be replaced by more productive firms. It is therefore very clear that firm dynamics do matter both in terms of micro and aggregate productivity growth. Further, new firms play a key role in this dynamic process not only because they replace less productive units, but also because they generate a higher degree of overall market competition.

On the whole, our results suggest that micro analysis is the proper complement to aggregate industry studies, as it provides a considerable insight into the causes of productivity growth. As to the policy implications of our analysis are concerned, the lesson seems to be quite straightforward: it claims for the promotion of an institutional environment more favourable to resource reallocation through entry and exit of firms in order to achieve a higher rate of production efficiency.

Appendix A. Parameter settings

See Table A1.

Table A1
Industry and firm parameter settings.

Parameter	Description	Technological regime	
		Routinized	Entrepreneurial
Industry			
D	Demand coefficient	65	65
ν	Discount rate	0.1	0.1
δ	Intensity of the selection mechanism	0.1	0.1
w^1 and w^2	Price of inputs	0.1 and 0.5	0.1 and 0.5
θ, ρ and φ	Parameters weighting past values	0.5	0.5
β	Adjustment rate of R&D	0.5	0.5
b_N	Technological opportunities to innovate	5.3	5.3
b_M	Technological opportunities to imitate	11.3	11.3
σ	S.D. of innovative draws	0.006	0.006
g^{max}	Maximum rate of innovative draws	0.01	0.01
μ_E	Mean of random entry rate (per scenario)	0.0105; 0.01075; 0.011; 0.01125; 0.0115	0.038; 0.03825; 0.0385; 0.03875; 0.039
σ_E	S.D. of random entry rate	0.001	0.004
X	Exit barrier	2	0
N	Start number of firms in the industry	65	65
Firms			
a^1 and a^2	Initial productivity of input 1 and 2	a^1 = [0.868, 1.101] and a^2 = [1.536, 1.745]	a^1 = [0.868, 1.101] and a^2 = [1.536, 1.745]
r	Initial R&D expenditure rate per unit of sales	r = [0.005, 0.0900]	r = [0.005, 0.0900]

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