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Sources of Concentration and Turbulence in Evolutionary Environments:

Simulations of Learning and Selection

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Abstract

This paper updates previous work on an evolutionary model of industrial competition and offers a link between formal and empirical studies of the relationship between technological change and industrial competition. It argues, using a simple formal representation of technological learning and market selection, it is possible to explain some of the variety of findings in the literature on industrial competition and technological change. The model shows that technological opportunities and technological entry-barriers play an important role in shaping patterns of industrial competition. Using repeated simulations, the model demonstrates that there is a non-linear relationship between market selection, technological learning and industrial dynamics. The analysis suggests that market concentration is largely dependent on the cumulative effects of past successes and random events, but market turbulence is dependent on the nature of technology. The paper explores some of the implications for modelling and empirical research from this simulation exercise.
1. Introduction

The importance of studying industrial competition from a dynamic perspective has been widely stressed in the literature (Dosi et al. 1997), and an increasing availability of micro time series has enabled researchers to directly measure the turnover (entries and exits) and mobility (size growth and market share volatility) of firms. However, although empirical studies have produced a few stylised facts on the general patterns of turnover and mobility of firms, theoretical models able to interpret the observed facts are still lacking and, as pointed out by Caves (1998), more needs to be done in relating these patterns to their underlying technological and market determinants.

This paper contributes to illustrate some aspects of the relationship between technological change and industrial dynamics by using a formal model of the Schumpeterian process of competition through innovation. The paper focuses on the conditions of innovation opportunity along a given trajectory of ‘normal’ technical change for established firms, the entry conditions of new innovators, and the intensity of the process of market selection through which new and old innovators compete in the market. By carrying out repeated simulations of the model under different parameter settings expressing such characteristics, the paper attempts to investigate the sources of market concentration and market turbulence; the latter defined by the volatility of market shares of continuing firms and the exit dynamics.

In the paper, the concept of technological regime (Nelson and Winter 1982, Dosi 1982) is used to link empirical studies and formal models of technical change and industrial competition. The aim of the paper is to establish which predictions can be made about the structures and dynamics of industrial competition on the basis of fairly simple and general principles. These principles have been identified in the model as mechanisms of technological learning and market selection, operating in distinct technological regimes. Technological regimes define some general properties of innovative processes that apply to distinct sets of production activities.

The approach taken in this paper differs from that proposed by Sutton (1998), whose solution was to identify general principles underlying the competitive mechanism of firms across the broad run of industries and derive, from these, the technological bounds to the set of all possible market configurations. It also differs from the approach of ‘history-friendly’ models, which have started to provide reconstruction of the event sequences that occurred in particular industries (Malerba et
al. 1999). The paper offers a third approach based on the concept of technological regimes.

2. Technological change and industrial competition: background

The empirical evidence of the relationship between technological change and industrial competition is ambiguous and, sometimes even, contradictory. Simple assumptions, such as technological change leads to concentration, are inaccurate. This section reviews some of the empirical findings that demonstrate the complexity of the link between technological change and industrial competition. The simulation model offered in Section 3 attempts to explore some of this complexity.

Industries are generally subject to intense processes of change. At the micro level, some firms undertake processes of market expansion, via internal or external growth, while others undergo a reduction in their market position and eventually exit the industry. At the same time, new firms continue to enter the market and compete, with varying success, with existing firms. At the aggregate level, the combination of these micro-dynamics shapes the structure of an industry and its evolution over time. At this level, it emerges that concentration in manufacturing industries is negatively related to market turbulence to a certain degree, as market shares volatility is greater in the least concentrated industries, and to the turnover from entry and exit (Caves 1998).

Innovation plays a crucial role in shaping the structures and dynamics of industries by creating opportunities for new firms to enter the market, and influencing their ability to survive and grow in the long run. However, it is only recently that empirical studies have begun to assess the influence of innovation upon industrial dynamics. Earlier studies within the ‘Schumpeterian hypotheses’ tradition have mainly focused on the effects of market structure on firm innovation, with mixed results (Cohen 1995). As stressed by Sutton (1998) although intense innovative activities lead most often to highly concentrated market structures, in some industries like capital goods and instrumentation, low levels of market concentration coexist with fairly high levels of innovative activity.

Only a limited number of studies in the most recent ‘post-Schumpeterian’ literature have empirically investigated the reversal causal link going from innovation to market competition (Acs and Audretsch 1990, Geroski 1994). Their findings do not
generally provide ‘stylised facts’ but rather pieces of circumstantial evidence, which require further investigation1. It is a ‘stylised fact’ that innovative firms have a better performance record than non-innovative (or less innovative) firms in a multiplicity of ways such as profitability, productivity, growth rates and market shares (Geroski and Machin 1992, Baldwin and Johnson 1995, Jensen and McGuckin 1997). Profitability asymmetries between innovators and non-innovators are notably higher and more persistent than the differentials in growth rates, as the latter are characterised by a highly erratic component (Geroski and Toker 1996, Geroski, Machin and Walters 1997). In addition, in high-tech sectors profitability asymmetries tend to be more pronounced, while innovation may result to be a less effective source of long-term asymmetries among innovators than in low-tech sectors (Geroski, and Machin 1992).

With regard to the technological determinants of market concentration and turbulence, the empirical evidence suggests that the innovative ability of new firms as compared to established firms in an industry is a fundamental explanatory factor of the observed patterns. That is, in order to account for the structures and dynamics of industrial competition, the technological conditions related to the prevalence of an ‘entrepreneurial regime’ as opposed to a ‘routinised regime’ (Winter 1984) need to be distinguished from the general level of technological opportunity in an industry2. Acs and Audretsch (1990), for example, found that concentrated market structures and low overall degrees of market turbulence, which was due to entries, exits, and market shares volatility, were associated with high general levels of technological opportunity and low levels of technological opportunity for new firms. However, other studies observed that volatility in the market shares of the leading firms in an industry tends to increase, and not decrease, relative to the intensity of R&D expenditure (Davies and Geroski 1997). This suggests that the technological determinants of market turbulence might vary between the ‘core’ and the ‘fringe’ of an industry.

In industrial economics, different theoretical approaches have emphasised different general mechanisms generating market concentration in an industry. Stochastic models in the Simon tradition have identified the sources of market concentration in (i) the cumulative effects of purely stochastic shocks in the dynamics

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1 A more extensive survey of the empirical and theoretical literature is in Marsili (2001).
2 The two regimes are also often labelled as ‘Schumpeter Mark I’ and ‘Schumpeter Mark II’ (Malerba and Orsenigo 1996).
of firm growth according to Gibrat’s Law and (ii) the existence of serial correlation in
firm growth processes. Because these conditions lead to an exponentially increasing
trend in market concentration, a process of firm entry, at constant rate, is introduced in
order to stabilise market concentration (Ijiri and Simon 1977)\(^3\). While in the models
of the Simon tradition inter-firm variety of performance is the outcome of purely
stochastic factors, other models have seen the existence of more persistent
asymmetries in the technological and organisational capabilities of firms as a
fundamental factor in generating market concentration. In particular, the equilibrium
models of dynamic competition (Jovanovic 1982, Hopenhayn 1992, Ericson and
Pakes 1996) assume that the process of Bayesian learning on the firm-specific
efficiency level under conditions of imperfect information leads to increasing market
concentration. Sutton (1998) proposes yet another approach based on a game-theory
framework. In Sutton’s approach, given the variety of inter-related search trajectories
associated with a certain technology, the level of market concentration depends on the
relative profitability of two general mechanisms in firms’ innovation strategies. One
is an ‘escalation’ mechanism through which firms compete in R&D expenditure along
a given search trajectory; the other is an ‘exploration’ mechanism through which firms
compete by exploring diverse technological trajectories.

In the evolutionary approach, the competitive status of a firm is determined by the
combination of stochastic factors, firm-specific capabilities, and industry-specific
characteristics of the technological and competitive environments in which firms
operate (Nelson and Winter 1982). Formal evolutionary models (Nelson and Winter
1982, Iwai 1984) envisage in the processes of Schumpeterian competition and market
selection the general mechanisms underlying the dynamics of industrial structures.
The ‘Schumpeterian’ principle of competition via innovation reflects the interaction
between the cumulative process of technological learning by established firms and the
process of ‘creative disruption’ by new innovators. The mechanism of ‘natural’
selection operates over time as the market determines which firms are profitable and
which are unprofitable (and which eventually exit the market) on the basis of their
diverse capabilities and decision rules.

\(^3\) A different approach to stabilise market concentration in stochastic models was taken by Kalecki
(1945), which introduced decreasing returns to scale in contrast with Gibrat’s Law.
The simulation model offered in this paper explores the influence on the structure and dynamic of industrial competition of stochastic factors in innovative processes, of the cumulative process of exploitation of technological opportunities along a given search trajectory, and of the entry conditions of new innovators. Following Nelson and Winter (1982), the model assumes that the micro-dynamics of learning and selection are shaped by some fundamental conditions typical of different technological and selection (or market) regimes, to a certain extent independent of the variety of idiosyncratic and discretionary behaviours of individual firms. Accordingly, cross-sectors differences in industrial structures and dynamics are explained as outcomes of underlying differences in the nature of technology on which innovative processes rely, and in the competitive conditions that determine the speed with which more successful firms displace the less successful.

In summary, the empirical literature reveals the complexity of the relationship between technological change and industrial dynamics. The model presented in this paper is an attempt to represent some of the mechanisms that underlay such a relationship and to illustrate the sources of market concentration and turbulence in an industry. The approach taken in interpreting the sectoral variety of observed patterns is based on the concept of technological regime, which provides an analytical framework linking empirical evidence and evolutionary modelling of technological change and industrial competition.

3. Description of the model
This section extends the analysis started in an earlier paper (Dosi et al. 1995) of the sources of cross-sectors differences in the pattern of industrial competition, sources that are related to the processes of technological learning and market selection. It does so by carrying out some econometrics of repeated simulation exercises of the model, by broadening the sets of the parameter settings, and by extending the analysis more fully to the exit dynamics.

In the model, it is assumed that the micro-dynamic of firm competitiveness is the outcome of an underlying process of innovation that is represented as a Poisson
stochastic process of arrivals\(^4\). Accordingly, the nature of the ‘technological environment’, or ‘technological regime’, in which firms innovate is expressed by the parameters of the Poisson stochastic processes of arrivals, respectively, for the innovation of established firms and the innovative entry of new firms. The Poisson parameter is inversely related to the expected arrival time between (i) two successive innovations, in the case of established firms (the parameter being identified as \(\delta^I\)) and (ii) two successive innovative entries in the case of new firms (the parameter being identified as \(\delta^E\)). Therefore, these two parameters represent the level of technological opportunity of incumbent firms and the level of technological opportunity of new firms (or inversely the strength of technological entry barriers), in a technological regime similarly to the Nelson and Winter’s model. In addition, it is assumed that technological regimes differ in the degree of cumulativeness of learning (Malerba and Orsenigo 1996). This condition is expressed by assuming that the ability of an established firm to exploit a general set of technological opportunities, varies, in term of the ‘size’ of innovation that the firm is able to achieve, according to three learning regimes: ‘Schumpeter Mark I’, ‘Intermediate’, and ‘Schumpeter Mark II’. In the ‘Schumpeter Mark I’ regime, incumbent firms do not learn, that is such an ability is equal to zero, and innovative dynamics are entirely driven by the entrepreneurial entry of innovative firms. In the ‘Intermediate’ regime of learning, incumbent firms learn technologically via a cumulative stochastic process, in the sense that the current level of competitiveness depends on the level already achieved, but with symmetrical abilities of firms to exploit the general conditions of technological opportunity. Last, highly cumulative processes of technological learning distinguish the ‘Schumpeter Mark II’ regime. In this regime the ability of a firm to exploit the general level of technological opportunity in an industry is a positive function of its current level of competitiveness, which reflects the firm-specific technological capabilities accumulated in past innovative activities.

The mechanism of market selection is represented through a ‘replicator’ dynamic of firm market shares\(^5\). More efficient firms expand their market shares, while less

\(^4\) This representation of innovative processes is also used by Aghion and Howitt (1992), Grossman and Helpman (1991), Silverberg and Lehner (1993).

\(^5\) In its original formulation the model also included a process of firms’ diversification across product markets, which however is not considered in this analysis. Therefore the focus is only on the mechanisms of learning and selection.
efficient firms reduce their market shares and eventually exit the market. The coefficient, A, of the replicator equation defines the intensity of the selection mechanism, that is the speed at which the market assign ‘rewards’ and ‘penalties’ to the firms for a certain distribution of firms’ characteristics. Although in a rather ‘stylised’ way, it reflects the basic conditions of demand that characterise the ‘market environment’ -or ‘market regime’- where firms compete (Further detail about the model can be found in the Appendix (see also Dosi et al. 1995)).

4. Results

In the analysis of the model’s properties, industrial structures are represented by various statistical indicators: the number of firms, the degree of market concentration measured by the ‘relative’ Herfindhal index of concentration\(^6\), and the degree of asymmetry in firm performance measured by the coefficient of variation in firm competitiveness, weighted by firm market share. Two indicators describe the properties of industrial dynamics: market turbulence, measured by the sum of variations, in absolute value, between time t and t+1 in the market shares of continuing firms, and the exit rate, calculated as the proportion of exiting firms between time t and t+1 on the number of firms surviving at time t.

For each selected combination of parameters under the diverse regimes of learning 10 repeated simulations of the model, over 1000 simulation times, were run. For each time series thus obtained, the average over the simulation times was calculated. A regression analysis of the average values of each industrial indicator was carried out with respect to the set of selected values of the system parameters. Under each regime of learning, the regression equation

\[
Y = \beta_0 + \beta_1 \delta^I + \beta_2 \delta^E + \beta_3 A
\]  

(1)

is estimated, where \(Y\) is any industrial indicator, among those mentioned above. The model is estimated through the OLS method. The estimates of the regression coefficients under the various learning regimes are reported in Tables 1, 2, and 3.

\(^6\) The measure of concentration that varies between zero and one is defined by \((nH-1)/(n-1)\), where the Herfindhal index, H, is the sum of squares of firms’ market shares.
**Table 1**
The effects of technological opportunity conditions and market selection on industrial competition: ‘Schumpeter Mark I’ regime

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Firms’ number</th>
<th>Concentration</th>
<th>Asymmetry</th>
<th>Turbulence</th>
<th>Exit rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tech. entry barriers</td>
<td>0.22 (0.0018)</td>
<td>0.66 (0.0000)</td>
<td>-0.90 (0.0000)</td>
<td>-0.89 (0.0000)</td>
<td>-0.54 (0.0000)</td>
</tr>
<tr>
<td>Selection</td>
<td>-0.69 (0.0000)</td>
<td>0.10 (0.1775)</td>
<td>-0.06 (0.1675)</td>
<td>0.24 (0.0000)</td>
<td>0.14 (0.0994)</td>
</tr>
<tr>
<td>(Constant)</td>
<td>1535.2 (0.0000)</td>
<td>0.0080 (0.0011)</td>
<td>0.0299 (0.0000)</td>
<td>0.0573 (0.0000)</td>
<td>0.0965 (0.0000)</td>
</tr>
</tbody>
</table>

Adj. R square 0.51 0.44 0.82 0.85 0.30

Note: OLS estimates of equation (1) (p-values in parentheses). Number of observations n=100.
Parameter settings: \( \delta^E = 1,2,3,4,5; \ A = 1, 1.5. \)

**Table 2**
The effects of technological opportunity conditions and market selection on industrial competition: ‘Intermediate’ regime

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Firms’ number</th>
<th>Concentration</th>
<th>Asymmetry</th>
<th>Turbulence</th>
<th>Exit rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tech. opportunity</td>
<td>-0.68 (0.0000)</td>
<td>0.65 (0.0000)</td>
<td>-0.12 (0.0265)</td>
<td>-0.31 (0.0000)</td>
<td>-0.36 (0.0000)</td>
</tr>
<tr>
<td>Tech. entry barriers</td>
<td>-0.64 (0.0000)</td>
<td>0.68 (0.0000)</td>
<td>-0.51 (0.0000)</td>
<td>-0.68 (0.0000)</td>
<td>-0.34 (0.0000)</td>
</tr>
<tr>
<td>Selection</td>
<td>-0.49 (0.0000)</td>
<td>0.44 (0.0000)</td>
<td>-0.54 (0.0000)</td>
<td>-0.09 (0.0460)</td>
<td>-0.32 (0.0000)</td>
</tr>
<tr>
<td>(Constant)</td>
<td>1183.34 (0.0000)</td>
<td>-0.2629 (0.0000)</td>
<td>0.1239 (0.0000)</td>
<td>0.0694 (0.0000)</td>
<td>0.1321 (0.0000)</td>
</tr>
</tbody>
</table>

Adj. R square 0.90 0.88 0.39 0.53 0.26

Note: OLS estimates of equation (1) (p-values in parentheses). Number of observations n=230
Parameter settings: \( \delta^I = 1,2,3; \ \delta^E = 1,2,3,4,5; \ A = 1, 1.5. \)
Table 3
The effects of technological opportunity conditions and market selection on industrial competition: ‘Schumpeter Mark II’ regime

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Dependent variables</th>
<th>Firms’ number</th>
<th>Concentration</th>
<th>Asymmetry</th>
<th>Turbulence</th>
<th>Exit rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tech. opportunity</td>
<td></td>
<td>-0.70</td>
<td>0.68</td>
<td>0.07</td>
<td>-0.27</td>
<td>-0.33</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0828)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Tech. entry barriers</td>
<td></td>
<td>-0.63</td>
<td>0.68</td>
<td>-0.40</td>
<td>-0.69</td>
<td>-0.24</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Selection</td>
<td></td>
<td>-0.61</td>
<td>0.49</td>
<td>-0.56</td>
<td>0.05</td>
<td>-0.30</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.2313)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>(Constant)</td>
<td></td>
<td>1199.45</td>
<td>-0.1099</td>
<td>0.0836</td>
<td>0.0478</td>
<td>0.0049</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0000)</td>
<td>(0.0001)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Adj. R square</td>
<td></td>
<td>0.93</td>
<td>0.86</td>
<td>0.43</td>
<td>0.50</td>
<td>0.19</td>
</tr>
</tbody>
</table>

Note: OLS estimates of equation (1) (p-values in parentheses). Number of observations n=320
Parameter settings: $$\delta^I = 1,2,3, \delta^E = 1,2,3,4, A = 1, 1.5, 2.$$

The effects of the system parameters upon industrial indicators are generally statistically significant. Therefore, differences in the properties of industrial structures and dynamics that emerge in the model among sectors are systematically related to the underlying technological and competitive conditions. More specifically, the R-square coefficients in Tables 2 suggest under the ‘Schumpeter Mark I’ regime, where entrant firms are the only sources of innovation, differences in technological and selective conditions have a greater effect upon market turbulence and performance asymmetry than on the number of firms and market concentration. The opposite is true when incumbent firms engage in cumulative processes of learning, under the ‘Intermediate’ and the ‘Schumpeter Mark II’ regimes. In this case, differences in technological and selective conditions have stronger effects upon the number of firms and market concentration than upon market turbulence and asymmetry. Finally, differences in exit rates among sectors with different system parameters are generally less noticeable than differences in the other statistical indicators.

The results of the model thus suggest that concentration and turbulence respond to different factors. Concentration seems to depend more strongly on cumulative effects of learning and random events. Turbulence seems to reflect more strongly
those characteristics of technology that create opportunities of innovative entry. Similar conclusions were reached by Caves when drawing on the empirical evidence on concentration and turbulence. Caves argued that mobility depends mainly on basic features of technology and demand, while concentration reflects the cumulative effects of past firm growth as shown by the random-processes models.

**Industry structures**

Tables 1, 2 and 3 show that in general high technological opportunity for established firms and high intensity of market selection reduce the number of firms able to survive in the market. The relationship between number of firms and technological entry barriers varies across regimes of learning, however. As shown in Tables 2 and 3, in presence of cumulative learning for established firms, under the ‘Intermediate’ and the ‘Schumpeter Mark II’ regimes, the number of firms decreases with an increase in technological entry barriers. In contrast, as shown in Table 1, when incumbents do not learn and innovation is entirely associated with entry, under the ‘Schumpeter Mark I’ regime, the number of firms increases with the level of technological entry barriers. These results suggest that when technological entry barriers are low, the process of cumulative learning enable the new innovators, having once entered the market, to cumulatively build upon their initial innovative success, and increase their probability to survive in the market. In contrast, when innovative entry is not combined with cumulative learning, the innovative abilities of new firms enhance the ‘selective pressure’ from the most successful entrants upon the established firms, and reduce the number of firms able to survive.

With respect to the Herfindhal index of concentration, Tables 1 to 3 show that, in general, technological opportunities and technological entry barriers are sources of increasing market concentration. These results are consistent with the empirical evidence showing that market concentration increases with the overall intensity of technological activity in an industry, while decreases with an increase in the relative innovative ability of new firms as compared to established firms (Acs and Audretsch 1990). Lastly, in Tables 1 to 3, industrial concentration increases with the intensity of market selection, especially so in presence of cumulative learning.

Asymmetry in firm performance decreases with an increase in the level of technological entry barriers, in all regimes of learning (Tables 1 to 3). Conversely, the
effect of the level of technological opportunity within an industry on the degree of asymmetry varies in sign across learning regimes, being it negative in the ‘Intermediate’ regime and slightly positive in the ‘Schumpeter Mark II’ regime. In addition, while the intensity of market selection significantly reduces asymmetry under general conditions of cumulative learning, the effect is not statistically significant when the innovation dynamic is driven only by entries.

Because of the varying sign of coefficients, the relationship between asymmetry and technological opportunities is analysed further, by estimating the regression model (1) in the ‘Schumpeter Mark II’ regime for each selected level of technological opportunity of entrants (Table 4).

Table 4
Conditional effects of technological opportunity and selection on performance asymmetry in the ‘Schumpeter Mark II’ regime

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>High barriers (a)</th>
<th>Medium-high barriers (b)</th>
<th>Medium-low barriers (c)</th>
<th>Low barriers (d)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tech. Opportunity</td>
<td>-0.23 (0.0214)</td>
<td>-0.18 (0.0317)</td>
<td>-0.01 (0.8783)</td>
<td>0.64 (0.0000)</td>
</tr>
<tr>
<td>Selection</td>
<td>-0.86 (0.0000)</td>
<td>-0.74 (0.0000)</td>
<td>-0.59 (0.0000)</td>
<td>-0.41 (0.0000)</td>
</tr>
<tr>
<td>Adj. R square</td>
<td>0.60</td>
<td>0.51</td>
<td>0.35</td>
<td>0.59</td>
</tr>
<tr>
<td>DF-residual</td>
<td>57</td>
<td>77</td>
<td>87</td>
<td>87</td>
</tr>
<tr>
<td>F</td>
<td>43.0</td>
<td>40.9</td>
<td>23.6</td>
<td>61.5</td>
</tr>
<tr>
<td>Sign. F</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Note: OLS estimates of equation (1) (p-values in parentheses). (a) $\delta=1$; (b) $\delta=2$; (c) $\delta=3$; (d) $\delta=4$.

The estimated coefficients described in Table 4 show the existence of a non-linear relationship between asymmetry, technological opportunity and technological entry barriers. When technological entry barriers are strong, high technological opportunities of cumulative learning appear to increase the ‘selective pressure’ and less innovative firms are more rapidly wiped out of the market. That is, in the absence of an external mechanism that persistently creates variety in an industry technological opportunity of cumulative learning reduces asymmetry. Conversely, when technological entry barriers are low, technological opportunities generated from
inside an industry increase asymmetry. In other words, above a certain threshold in the general level of technological opportunity for both incumbents and entrants, cumulative learning does not reduce asymmetries, but strengthens the competitive advantage of the most successful firms, both incumbents and entrants.

The empirical evidence on the technological determinants of asymmetry in firm economic performance is limited, as discussed in Section 2. Some findings are available for measures of asymmetries between innovators and non-innovators, as a whole, however (Geroski, and Machin 1992). These empirical findings are not entirely comparable with the outcomes of the model, which refer to asymmetries among all firms. The empirical evidence seems to suggest that performance asymmetries between innovators and non-innovators increase with the level of opportunity in the industry, while asymmetries between innovators may decrease as the impact of innovative output on performance becomes lower in more innovative sectors (Geroski, and Machin 1992).

**Industry dynamics**

In Tables 1 to 3, high technological opportunities within an industry, and high technological entry barriers reduce the volatility in the market shares of continuing firms. This outcome is consistent with the empirical evidence suggesting that the general level of turbulence (including entries and exits, however) decreases with the technological opportunities in the industry and increases with the ability of new firms to access such opportunities (Acs and Audretsch 1990).

With regard to market selection, the results of the model show that the effect of market selection upon turbulence varies across regimes. It is positive in the ‘Schumpeter Mark I’ regime, while it is either slightly negative, or not statistically significant, in regimes of cumulative learning. For this reason, the relationship is explored further by estimating the regression model (1) for each selected level of opportunity for entrants in the ‘Schumpeter Mark II’ regime (Table 5).
### Table 5
**Conditional effects of technological opportunity and selection on market turbulence in the ‘Schumpeter Mark II’ regime**

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>High barriers (^{(a)})</th>
<th>Medium-high barriers (^{(b)})</th>
<th>Medium-low barriers (^{(c)})</th>
<th>Low barriers (^{(d)})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tech. Opportunity</td>
<td>-0.61 (0.0000)</td>
<td>-0.57 (0.0000)</td>
<td>-0.49 (0.0000)</td>
<td>0.01 (0.8908)</td>
</tr>
<tr>
<td>Selection</td>
<td>-0.54 (0.0001)</td>
<td>-0.18 (0.0735)</td>
<td>-0.01 (0.8726)</td>
<td>0.78 (0.0000)</td>
</tr>
<tr>
<td>Adj. R square</td>
<td>0.31</td>
<td>0.30</td>
<td>0.22</td>
<td>0.59</td>
</tr>
<tr>
<td>DF-residual</td>
<td>57</td>
<td>77</td>
<td>87</td>
<td>87</td>
</tr>
<tr>
<td>F</td>
<td>14.4</td>
<td>17.6</td>
<td>13.7</td>
<td>65.9</td>
</tr>
<tr>
<td>Sign. F</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Note: OLS estimates of equation (1) (p-values in parentheses). \(\delta^E=1\); \(\delta^E=2\); \(\delta^E=3\); \(\delta^E=4\).

From Table 5, it emerges that market selection tends to stabilise the market when technological entry barriers are high, while they tend to increase the volatility in firm market shares when technological entry barriers are low. Interestingly also the influence of technological opportunity on turbulence varies with the strength of technological entry barriers. While technological opportunities reduce significantly turbulence in presence of high entry barriers to innovation, the effect becomes statistically non-significant (and even slightly positive) when those barriers are low. Above a certain threshold in the general level of technological opportunities for both incumbents and entrants, market selection and cumulative learning enhance the competitive advantage of the more successful firms, either newly entered or established firms, leading to high volatility in market shares. The results of the model, thus, suggest that the relationship between technological change and turbulence is non-linear. This is to a certain extent consistent with the observation that the relationship may vary when a measure of turbulence in the market shares of leading firms is considered. In this case, the positive effect of technological opportunities within an industry upon turbulence is observed (Davies and Geroski 1997).

Similar results are obtained when turbulence refers to the process of firm exit. Tables 1 to 3 show that, in general, high technological opportunity and high technological entry barriers lead to low exit rates. Cumulative learning in presence of
high barriers to innovative entry tends to stabilise the market, not only in terms of market shares’ mobility, but also in terms of the turnover of firms. In general, the exit pattern in the model is consistent with the empirical evidence illustrated by Acs and Audretsch (1990) on the general level of turbulence across industries.

With regard to market selection, its effect on the exit rate varies among regimes of learning. In the ‘Schumpeter Mark I’ regime, where firms compete exclusively on the basis of the innovation they introduce by entering the market, market selection increases the exit rate (Table 1). Conversely, in regimes of cumulative learning, a more effective mechanism of market selection, in the sense that it more rapidly assigns rewards and penalties to firms, reduces exit rates (Tables 2 and 3). That is, when established firms fail to exploit new technological opportunities, a highly selective ‘market environment’ increases the speed with which less successful firms are wiped out from the market. However, selective market conditions increase the ability of firms to survive in the market when firms are able to cumulatively exploit their technological capabilities.

In order to summarise the general pattern of industrial structures and dynamics that emerge from the preceding outcomes, the correlation matrix among the various industrial indicators is calculated for diverse regimes of learning (Tables 6 and 7).

### Table 6
Correlation matrix of the indicators of industrial competition: ‘Schumpeter Mark I’ regime

<table>
<thead>
<tr>
<th></th>
<th>Firms’ number</th>
<th>Concentration</th>
<th>Asymmetry</th>
<th>Turbulence</th>
<th>Exit rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firms’ number</td>
<td>1</td>
<td>-0.38 (0.000)</td>
<td>-0.43 (0.000)</td>
<td>-0.33 (0.001)</td>
<td>-0.11 (0.263)</td>
</tr>
<tr>
<td>Concentration</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asymmetry</td>
<td></td>
<td>-0.37 (0.000)</td>
<td></td>
<td>-0.67 (0.000)</td>
<td>-0.47 (0.000)</td>
</tr>
<tr>
<td>Turbulence</td>
<td></td>
<td></td>
<td>0.81 (0.000)</td>
<td></td>
<td>0.44 (0.000)</td>
</tr>
<tr>
<td>Exit rate</td>
<td></td>
<td></td>
<td></td>
<td>0.56 (0.000)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Number of observations n = 100
In general, conditions of high concentration, low asymmetry, low turbulence and low exit rate, all tend to occur simultaneously in an industry. However, while these conditions tend to be also associated with a small number of firms in a regime of cumulative learning, they are associated with a relatively higher number of firms in the ‘Schumpeter Mark I’ regime. In particular, it emerges that industries with highly concentrated market structures display relative stability, both in terms of volatility of market shares and exit rates. This pattern is consistent with the empirical evidence discussed by Caves (1998).

In the previous discussions, the effects of the level of technological opportunity and technological entry barriers on industrial competition have been examined. However a direct comparison of the properties of industrial structures and dynamics between the different processes of learning assumed in the model can also be established. In order to examine how the presence of cumulative learning affects patterns of industrial competition, a dummy variable - labelled ‘learning’ - is added to the regression model. This variable is set equal to zero in the ‘Schumpeter Mark I’ regime, and to one in the ‘Schumpeter Mark II’ regime (Table 8).

<table>
<thead>
<tr>
<th></th>
<th>Firms’ number</th>
<th>Concentration</th>
<th>Asymmetry</th>
<th>Turbulence</th>
<th>Exit rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firms’ number</td>
<td>1</td>
<td>-0.88</td>
<td>0.31</td>
<td>0.37</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Concentration</td>
<td>1</td>
<td>-0.58</td>
<td>-0.70</td>
<td>-0.64</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Asymmetry</td>
<td>1</td>
<td>0.64</td>
<td></td>
<td>0.76</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.002)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Turbulence</td>
<td>1</td>
<td></td>
<td>0.75</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Exit rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>

Note: Number of observations n = 320
Table 8
Learning, industrial structures and dynamics

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Number of firms</th>
<th>Concentration</th>
<th>Asymmetry</th>
<th>Turbulence</th>
<th>Exit rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning</td>
<td>-0.62 (0.000)</td>
<td>0.41 (0.000)</td>
<td>0.56 (0.000)</td>
<td>-0.08 (0.032)</td>
<td>-0.08 (0.080)</td>
</tr>
<tr>
<td>Entry barriers</td>
<td>-0.27 (0.000)</td>
<td>0.39 (0.000)</td>
<td>-0.43 (0.000)</td>
<td>-0.61 (0.000)</td>
<td>-0.16 (0.001)</td>
</tr>
<tr>
<td>Selection</td>
<td>-0.34 (0.000)</td>
<td>0.30 (0.000)</td>
<td>-0.49 (0.000)</td>
<td>0.11 (0.003)</td>
<td>-0.23 (0.000)</td>
</tr>
<tr>
<td>(Constant)</td>
<td>1366.7 (0.000)</td>
<td>0.003 (0.949)</td>
<td>0.058 (0.000)</td>
<td>0.042 (0.000)</td>
<td>0.105 (0.000)</td>
</tr>
<tr>
<td>Adj.-R square</td>
<td>0.69 (0.49)</td>
<td>0.52 (0.41)</td>
<td>0.41 (0.09)</td>
<td>0.41 (0.41)</td>
<td>0.41 (0.41)</td>
</tr>
<tr>
<td>DF</td>
<td>416</td>
<td>416</td>
<td>416</td>
<td>416</td>
<td>416</td>
</tr>
</tbody>
</table>

Note: OLS estimates (p-values in parentheses)

The presence of cumulative learning implies: (a) more concentrated market structures, in terms of both lower number of firms, and higher concentration in market shares; (b) higher asymmetry in firm performance; and (c) slightly lower turbulence and exit rates. Similar results on the effects of cumulative processes of learning on market concentration and efficiency asymmetry were obtained by Oltra (1997). In addition, Table 8 shows that differences in the volatility of market shares reflect to the greatest extent, differences in the ability of new firms to exploit new opportunity of innovation (i.e. in the level of technological entry barriers), while differences in exit rates reflect, above all, differences in the intensity of market selection.

Technological regimes and industrial competition

The properties of industrial structures and dynamics derived above using the model can be mapped into the empirical technological regimes that emerge in the industrial system (Pavitt 1984, Malerba and Orsenigo 1996, Marsili 2001). In the model, the nature of technology in industries typical of a ‘Schumpeter Mark II’ regime, such as for example science-based industries, can be represented by the combination of high technological opportunity, high technological entry barriers and high cumulativeness of learning. These conditions lead to high market concentration,
small numbers of firms, low asymmetry in firm performance, low market turbulence and low exit rates, but with strong differences in exit rates that are high for young firms and particularly low for old firms. The opposite conditions characterise a regime where innovation is introduced mainly from outside the industry with low technological opportunity for established firms, typical of more traditional industries in the ‘Schumpeter Mark I’ regime (Malerba and Orsenigo 1996).

In addition to the distinction between a ‘Schumpeter Mark I’ and ‘Schumpeter Mark II’ regime of innovation, the model contributes to illustrate the patterns of industrial competition in industries in which a high level of technological opportunity within an industry coexists with high levels of opportunity of innovative entry. These conditions are typical of non-electrical machinery and instrumentation industries. In the model, the nature of technology of these industries can be represented by combining medium-high opportunities of cumulative learning for established firms (in the Intermediate regime) with low technological entry barriers. Under these conditions, the model generates industrial patterns characterised by low market concentration, high asymmetry in firm performance, high market turbulence and high exit rates, the exit rates being fairly uniform across age classes.

A direct implication of these results concerns the interpretation of the non-linear relationship between market concentration and R&D intensity observed in the empirical literature (Cohen 1995). The model’s findings suggest that such a relationship is conditional on the level of technological entry barriers. The low levels of concentration observed in fairly technologically intense sectors like non-electrical machinery and instrumentation (Sutton 1998) are interpreted in the model as an outcome of the combination of medium-high technological opportunity, medium cumulativeness of learning, and low technological entry barriers. This is illustrated in more detail by Figure 1 representing the simulated market concentration under different combinations of entry barriers and cumulativeness of learning in high-tech industries. Figure 1, also shows that while market concentration decreases with higher innovative abilities of entrant firms in both the ‘Schumpeter Mark II’ and ‘Intermediate’ regime, it decreases more rapidly when cumulativeness is lower.

7 This last property is derived from preliminary results presented in Dosi et al. (1995).
8 See note 7.
Figure 1
Market concentration in alternative regimes with high technological opportunity

Notes:
Average values over 10 simulations

= High entry barriers; High cumulativeness,
- - - = Low entry barriers; High cumulativeness,
- - - - - - = Low entry barriers; Medium cumulativeness.

The interpretation suggested above is complementary to that proposed by Sutton (1998), in which the relationship between R&D intensity and market concentration is conditional on the variety of technological trajectories. Sutton demonstrates that in R&D intense industries a concentrated market structure emerges when only one technical trajectory is available or products are close substitutes as dominant firms ‘escalate’ in R&D spending along similar trajectories of product innovation. However, R&D intense industries display low levels of market concentration when many technical trajectories coexist or products are not close substitute, as a number of small firms can successfully ‘explore’ divergent R&D trajectories, conditions typical of non-electrical machinery and instrumentation industries.

The characterisation of regimes that is applied in this paper differs to a certain extent from that used by Nelson and Winter (1982). Nelson and Winter identify the ‘entrepreneurial’ regime with a science-based technology, in which learning is non-cumulative and depends entirely on the exogenous stage of scientific advances. The characterisation of a ‘science-based’ regime appears a complicated one because of the
differentiated nature of the contribution of scientific advances to industrial innovation (Pavitt 1991). What the model shows is that in a science-based regime the combination of high technological opportunity of cumulative learning and high technological entry barriers, these latter originating in the specificity of knowledge application across production processes (Marsili 2001), generates a tendency towards concentrated and stable market structures. However, when new scientific findings are directly translated into industrial innovation, the combination of high technological opportunities for both established and entrant firms, which originate in the ‘technological richness’ of new product applications of a ‘generic’ knowledge base, leads to low market concentration and high turbulence. Under these conditions, high technological entry barriers may then endogenously emerge as an outcome of the strong cumulativeness of learning and the advantage acquired by the first entrants.

7. Conclusions
By using the concept of technological regimes, this paper attempted to link theoretical and empirical studies of the relationship between technological change and industrial dynamics. This paper has updated a previous work on an evolutionary model of industrial competition. Through econometrics of repeated simulation exercises of the model, this paper reached more conclusive and extensive results concerning the influence of the technological and market environments in which firms operate on the sectoral patterns of industrial structures and dynamics. This paper demonstrated that a simple formal representation of technological regimes contributes to explain the cross-sectors variety of observed patterns. In particular, the following properties were derived from the model’s simulation.

i) The combined effect of technological opportunity and entry barriers is important in explaining patterns of industrial competition.

ii) Technological learning and market selection exert non-linear effects on industrial competition.

iii) Static and dynamic measures of industrial competition respond to different explanatory factors.

iv) Concentrated market structures tend to be associated with low degrees of turbulence both in market shares volatility and exit rates.
With regard to the first two points, it was shown that, first, the combination of high technological opportunities and high technological entry barriers is important in leading to high concentration and low turbulence, and market selection strengthens this effect. Second, that in sectors of high technological opportunities, a dispersed and turbulent market structure emerges in presence of low technological entry barriers, and under these conditions market selection contributes to increase turbulence.

This paper explores a research area focusing on the interpretation of sectoral difference in industrial structures and dynamics based on the characteristics of technological regimes. It suggests an approach of analysis linking simulation exercises of fairly simple formal models to the empirical evidence on the characteristics of firms’ innovative processes and their import for industrial dynamics. This approach complements ‘history friendly’ models and Sutton’s bounds approach.
Appendix: Simulation model

Technological learning

For an incumbent firm, it is assumed that a parameter of competitiveness, $A_t$, in principle summarising both productivity and product quality, increases, by a constant proportional factor, whenever an innovation takes place, that is:

$$A_t = A_0 \mu^\tau$$

(2)

where the parameter $\mu$ defines the ‘size’ of an innovation and the index $\tau$ identifies the time sequence of the innovation process. Further, the innovation sequence is assumed to follow a Poisson stochastic process of arrivals with parameter $\delta^I$. This parameter then represents the ‘ease’ of innovation. The Poisson process of arrivals, defined over a continuous time variable, implies that the number of innovations occurring over a discrete time interval, $(t, t+1)$, is a stochastic variable which is distributed according to a Poisson of parameter $\delta^I$. As each innovation produces a proportional increment in firm productivity, equal to $\mu$, the total variation in firm productivity from time $t$ to time $t+1$, is given by

$$\Delta a_t = \mu h_t a_t$$

(3)

where $a_t$ is the firm productivity at time $t$, and $h_t$, the number of innovations in the considered period of time, is a random variable distributed as a Poisson with parameter $\delta^I$.

The model introduces the generalisation that the outcome of innovation, $\mu$, is a generic function of the current level of firm competitiveness. Equation (3) can thus be rewritten as:

$$\Delta a_t = \frac{m(a_t)}{\lambda^I} h_t a_t$$

(4)

where $\lambda^I$ is a scale parameter. Therefore, changes in firm competitiveness, according to a Markov stochastic chain, are the outcomes of a continuous process of innovation occurring at a rate $\delta^I$, and size, in terms of effect on competitiveness, $m(a_t) / \lambda^I$.

From equation (4), it follows that the expected relative increment in firm competitiveness that results from innovation is equal to:

$$E\left(\frac{\Delta a_t}{a_t}\right) = \frac{m(a_t)}{\lambda^I} \delta^I$$

(5)
Therefore, two components can be distinguished in the expected outcome of firm innovation: one component is common to all the firms in a sector, $\delta_I/\lambda_I$, and expresses the level of technological opportunity for incumbent firms in terms of the ‘scope’ and ‘ease’ of innovation. The other component, $m(a_i)$, is specific to the firm and reflects the firm’s accumulated technological capabilities and, therefore, its specific ability to exploit a general set of innovation opportunities.

On the bases of equation (4) different ‘regimes’ of learning are distinguished that capture various degrees of cumulativeness of innovative processes. In a ‘Schumpeter Mark I’ regime incumbent firms do not learn, that is:

$$m(a_i) = 0.$$  \hfill (6a)

In an ‘Intermediate’ regime incumbents firms have symmetrical ability to exploit a given set of technological opportunity, that is:

$$m(a_i) = \mu \equiv 1.$$  \hfill (6b)

Finally, in a ‘Schumpeter Mark II’, the innovative ability of a firm increases with its current level of competitiveness. This is expressed by the condition:

$$m(a_i) = 1 + \ln \left( 1 + \frac{a_i}{\bar{a}_i} \right).$$  \hfill (6c)

where $\bar{a}_i$ is the average competitiveness of incumbent firms in the market, weighted by their market shares, $f_i$, that is:

$$\bar{a}_i = \sum_{i} a_i f_i.$$  \hfill (7)

**Innovative entry**

In any regime of learning, new firms enter the market at a constant rate with a stochastic disturbance. The initial level of competitiveness of a new firm entering the market at time $t_0$ is defined by:

$$a_{t_0} = \left( 1 - \kappa + \frac{h_{t_0}}{\lambda^E} \right) \cdot a_{t_0}$$  \hfill (8)

where $h_{t_0}$ is a stochastic variable, independent and identically distributed among firms and over time, following a Poisson distribution of parameter $\delta^E$, and $\lambda^E$ is a scale parameter. Accordingly, the expected relative increment of competitiveness that a new firm is able to reach via innovation with respect to the existing average level in
the market depends on the parameter $\kappa$, which reflects the strength of generic entry barriers, and on the ratio, $\delta^E/\lambda^E$, which reflects the level of technological opportunity for new firms, or inversely the strength of technological entry barriers in an industry.

**Market selection**

The mechanism of market selection is represented through a modified version of the replicator dynamic introduced by Silverberg, Dosi and Orsenigo (1988). It is thus assumed that the market share of a firm, $f_i$, changes over time according to:

\[
\Delta f_i = A \cdot \left( \frac{a_{i,t}}{\bar{a}_{t}} - 1 \right) \cdot f_i
\]

(9)

If, as an outcome of the competitive processes expressed by the replicator dynamic, the firm’s market share falls below a minimum threshold the firm exits the market.
References


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