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The impacts of Technological Change, Industry Structure and Plant Entry/Exit on industry efficiency growth

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ABSTRACT

In this paper, we provide a theoretical framework combining both the theory of adoption and industry evolution to explore the different sources of industry efficiency growth. The objective is to investigate which of the explanatory variables can explain inefficiency. The theoretical and simulation results of this study show that the inter-firms efficiency variance exerts a substantial impact on industry efficiency. Productivity change within individual plant (via adoption and learning) is a major source of efficiency growth in the industry. Exit usually improves aggregate efficiency as less efficient plants leave industries. The impact of entry is less clear since it depends on the efficiency levels of entrants. Finally, the role of competition in generating economic efficiency is strongly confirmed. Our theoretical findings confirm and extend others in the empirical studies.

INTRODUCTION

Significant differences in levels of efficiency and efficiency growth rates exist across industries, regions and countries. Technical efficiency arises when a firm makes the best use of its inputs and technologies. The study of efficiency is important, especially in the context of developing economies where firms and industries are far from the "best practice level" of efficiency given a level of technology. (Pitt and Lee (1981); Nishimuzu and Page (1982); Martin and Page (1983; Corbo and de Melo (1986); Chen and Tang 1987; Tybout (1991); Tybout and Westbrook (1995); Clerides at al (1998); Lundvall and Battese (2000) and others...). Tybout (2000), reports that in developing countries, the mean technical efficiency levels are around 60 to 70 per cent of the best practice frontier, in developing countries,. This is due to the high cross-firm variance in efficiency levels (Pack (1988), Blomstrom and Kokko (1998), etc…) Many other studies for sub-Saharan Africa argued that the problems of technical inefficiency are likely to be most important…

Empirical studies explaining these differences in aggregate efficiency across industries and focusing on the contribution of different processes to industry efficiency growth have grown dramatically in recent years as plant-level, longitudinal databases have been developed (Baily et al 1992; Bartelsman and Drhymes 1992; Baily, Hulten and Campbell (1992), Bartelsman and Dhrymes (1994); Dwyer (1995, 1997); Bartelsman and Doms 1997 ; Foster et al 1998; Jensen et al 1998). The evolution of aggregate industry efficiency is usually explained by three mechanisms:
(a) *Intra-plant factors* (changes in productivity via adoption of innovation, learning, R&D…): these empirical studies have shown that technological changes lead to increased efficiency for the firm adopting it, but may also raise the distance between the frontier and the average firms. This may result in a decline in average efficiency of the industry. Thus, the effect of technology on efficiency is ambiguous (see Caves 1992).
(b) *Inter-plant factors* (the efficiency variance of plants and industry structure): the most significant finding of these studies is the large variance in efficiency levels between plants in the same industry as well as the persistence of this variance. These differences in efficiency have been shown to exert a substantial impact on industry efficiency.
(c) *Creative destruction factor* via plant entry and exit: Empirical analysis of implications of turnover for efficiency dynamics has been recently provided by Haltiwanger (1997) using plant-level manufacturing data from the U.S.; Aw, Chen and Roberts (1997) using firm-level data from Taiwan; Tybout (1996) and Liu and Tybout (1996) using data from Columbia, Chile, and Morocco; and Griliches and Regev (1995) using data from Israel and Baldwin (1995) using data from Canada. These studies have shown that exit usually improves aggregate productivity as less efficient plants leave industries. The impact of entry is less clear since it depends on whether efficiency level of entrants is higher or lower than the average efficiency of the industry.

Other studies (Caves (1992)) have classified the determinants explaining inter-industry differences in efficiency into four *intra-industry factors*. These four factors are:

(a) *Competitive conditions* (including factors related to market structure such as concentration of the industry, import competition and export intensity).
(b) *Structural heterogeneity* (those that cause competing units to exhibit heterogeneous levels of efficiency in the long run and include capital intensity, product differentiation, consumer preference and demand elasticity, and diversity of plant scale).
(c) *Dynamic disturbances* (technology adoption, learning and intensity of R&D expenditure).
(d) *Regulation: A*mong the regulatory policies affecting efficiency are tariff protection and policies that control the entry of firms in an industry. High entry costs and market interventions like artificial entry barriers not only reduce the amount of entry but also encourage incumbents with lower efficiency to remain in the market. This increases the efficiency dispersion in the market, reducing the average level of efficiency. Foster et al (1998), show that the relative size of these components of the industry efficiency change, a finding that depends rather heavily on the method used to decompose aggregate efficiency as well as on the time period examined.

Theoretical attempts to explain the contribution of these different processes to industry efficiency growth are much scarcer than empirical studies. They typically focus on industry structure, initial levels of efficiency, the quality of inputs to production and also on some measure of technical change (Beeson 1987; Fogarty and Garofalo 1988; Williams and Moomaw 1989 and 1991). These studies assume that efficiency change results from identical, perfectly competitive firms responding homogeneously to economic forces of various kinds. This often makes aggregate models inconsistent with observed behaviour at the plant level and obscures the individual process and different mechanisms that generate industrial efficiency change. Though, many theoretical fields, where imperfect competition and firm heterogeneity are the norm, focus on these factors separately, like the theory of innovation and adoption for intra-plant factors (Feder [1980], Fudenberg and Tirole (1985), Feder, Just and Silberman [1984], Jensen (1992), Hoppe (2000) and others), the theory of industrial organization for inter-plants factors (Dunne et al 1989; Dom 1993; Baldwin and Rafiquzzaman 1994; Baldwin 1995; Doms et al 1995; Caves 1997, Nelson and Winter 1982; Metcalfe 1992), and the theory of industry evolution and creative destruction for entry and exit Lippman and Rumelt (1982), Gort and Klepper (1982), Dixit and Shapiro (1986), Jovanovic and Lach (1989), Ericson and Pakes (1989, 1990), Lambson (1991,1992), Hopenhayen (1992) D.B.Audretsch et Talat Mahmood (1994) and others).

Based on these considerations, the aim of this paper is to identify and sort out the role of different factors that affect the efficiency of firms, the average efficiency of the industry and to determine the nature and magnitude of the contribution of each factor to aggregate efficiency growth. In order to do that, we use a model of plant-level heterogeneity, in which we combine the theory of adoption, industrial evolution and creative destruction. The paper is organized as follows. Section 1 presents the model. In Section 2, industry equilibrium is defined, while Section 3 provides the analysis of the model. Section 3 is divided into three parts, with the first focusing on structure, the second developing comparative statistics. Section 5 provides final remarks.

1- The Model:

In this section we present a dynamic model of adoption and passive learning in which we explicitly formalize the firms' entry and exit decisions in a market for a differentiated product with monopolistic competition. Our model is similar to Hopenhayen (1992, 1993) and Jovanovic and MacDonald (1994) in that firms are faced with individual efficiency shocks, which is the only source of uncertainty. On the basis of these shocks, firms decide when to optimally exit the industry. The process of market selection then leads to exit of firms afflicted by unfavourable shocks, often opening up room for entrants. A central feature of the model is that an entrant does not know its own cost structure. Rather, relative efficiency of each entrant is discovered through the process of learning from actual market experience. Entrants who discover that their efficiency level exceeds their expectations will expand the scale of their business, whereas those discovering that their post-entry performance is less than commensurate with their expectations will exit from the industry. Entry requires an investment that is non-recoverable and becomes a sunk cost thereafter.

Each firm produces a unique brand of the same generic product. Hence, at any given time *t,* the number of firms operating, *n*(*t*), equals the number of varieties available to consumers. We assume a Dixit and Stiglitz utility function:

$$U = \int_0^\infty e^{-rt} (x_0(t) + \log C(t)) \, dt \qquad (1)$$

Where $x_0(t)$ is the consumption of the numeraire in time *t,* and $C(t)$ is the consumption index of the Dixit-Stiglitz type

$$C(t) = \left(\int_0^{n(t)} y_j(t)\alpha \quad dj \right)^{1/\alpha} \qquad where \quad 0 < \alpha < 1 \tag{2}$$

Where $y_j(t)$ is the amount of variety j of the differentiated product demanded by a consumer at time t. The aggregate demand function $Y_j(t)$ for variety j at time t is:

$$Y_j(t) = \frac{p_j(t)^{1/(\alpha-1)}}{\int_0^{n(t)} p_i(t)^{\alpha/(\alpha-1)} \, di} E \tag{3}$$

where E is equal to the total instantaneous expenditure on the differentiated product and $p_j(j)$ is the price of variety j at time t. The demand function (3) is isoelastic with the elasticity of demand $\sigma = 1/(1-\alpha)$. Efficiency is obtained by minimizing the cost incurred at each level of activity. The technology used by the firm is described by the cost function $C_j^x(t) = \hat{c}_j^x(t) \; y_j(t) + F$, where F is the fixed cost and $\hat{c}_j^x(t)$ is the marginal cost. Across firms, $c\hat{x}$'s are random and take three possible values $\hat{c}_j^o(t)$, $\hat{c}_j^l(t)$ and $\hat{c}^h$, with $\hat{c}^h < \hat{c}_j^l(t) < \hat{c}_j^o(t)$. Firms experiencing $\hat{c}_j^o(t)$ are the lowest-efficiency (*o*-) firms, which still use the old technology. Those experiencing $\hat{c}^h$ are the high-efficiency (*h*-) firms which have adopted the new technology and use it at the "best practice" level of technical efficiency for which it was designed. Finally, *l*-firms experiencing $\hat{c}_j^l(t)$ have adopted the new technology but are still engaged in learning, adaptation and search efforts in order to have successful implementation and to use the new technology efficiently.

It is assumed that firms discover their type at the beginning of each period. A firm j of type x ($x = o, l, h$) which stays maximizes profits $\pi_j^x(t) = p_j(t) \; y_j(t) - \hat{c}_j^x(t) \, y_j(t) - F_t$, subject to the demand curve it faces given in (3). The optimal pricing rules for firm j of type x is: $p_j(t) = \hat{c}_j^x(t) \left(\frac{\theta}{1+\theta} \right)$

where $\left(\frac{\theta}{1+\theta} \right)$ is the mark-up over the marginal cost and $\theta = \frac{\alpha}{1-\alpha}$.

Using this pricing rule, the profit expression of the firm j of type x is:

$$\pi_j^x(t) = \frac{c_j^x(t) \, E}{(\theta+1) cm_t \; n(t)} - F_t \quad \text{where} \quad cm_t = \frac{1}{n(t)} \int_0^{n(t)} c_j^x(t) \quad dj$$

Let cm_t is the cross firms average efficiency level during the period t. cm_t is the most commonly reported summary measure of industry's performance. $cm_t = \frac{1}{n(t)} \int_0^{n(t)} c_j^x(t) \; dj$

Let cm_t^l, cm_t^o and ch be respectively the average efficiencies of (*l*-) and *o*-firms in this period.

$$cm_t^l = \frac{1}{n^l(t)} \int_{n^h(t)}^{n^h(t)+n^l(t)} c_j^l(t) \quad dj \quad \text{and} \quad cm_t^o = \frac{1}{n^o(t)} \int_{n^h(t)+n^l(t)}^{n(t)} c_j^o(j) \quad dj \tag{4}$$

The aggregate efficiency "cm" can be calculated as the weighted average of efficiency levels for (*o*-), (*l*-) and *h*-firms. $cm_t = c^h n^h(t) + cm_t^l\; n^l(t) + cm_t^o\; n^o(t)$

We assume that $c_j^x(t) = A(j\,,\,t)\; cm_t$, with $A(j\,,\,t) \geq 0$ for all *j*, is a continuous and monotonously decreasing function of the firm index *j*. That is, firms are ranked in terms of this parameter in such a way that more efficient firms have a lower index number. We assume a specific functional form for $A(j,t)$, namely:

$$A(j,t) = 1 + \varepsilon(t)\left(\frac{1}{2} - \frac{j}{n(t)}\right) \qquad 0 < \varepsilon(t) < 2 \tag{5}$$

Where $\varepsilon(t)$ is an endogenous parameter measuring the industry concentration. We can see that higher values of this parameter imply a greater inter-firm variance in efficiency. As $\varepsilon(t)$ converges to zero the industry becomes homogenous and $A(j,t)$ converges to 1.

Finally we can see that in the expression $c_j^x(t) = A(j,t)\, cm_t$ the type of the firm does not matter. To make difference between (*l*-) and *o*-firms (which is necessary to avoid undetermined form and to solve the model) we assume that $c_j^l(t) = l.A(j,t)\, cm_t\,(t)$ and $c_j^o(t) = o.A(j,t)\, cm_t\,(t)$. *l* and *o* are two different positive values very close to 1. (*l* > *o*). This hypothesis does not affect results since *l* and *o* are instrumental variables which will disappear by simplification).

The expressions of the (*h*-), (*l*-) and *o*-firms profits can be written as follow:

$$\pi^h(t) = \frac{ch\;E}{(\theta+1)\;n(t)} - F_t = \frac{ch\;E}{(\theta+1)\,(c^h\,n^h(t) + cm_t^l\,n^l(t) + cm_t^o\,n^o(t)} - F_t$$

$$\pi_j^l(t) = \frac{l\;A(j,t)\;E}{(\theta+1)\;n(t)} - F_t = \frac{l\,.\;A(j\,,\,t)\;cm_t\;\;E}{(\theta+1)\,(c^h\,n^h(t) + cm_t^l\,n^l(t) + cm_t^o\,n^o(t)} - F_t \quad ;$$

$$\pi_j^o(t) = \frac{o\;A(j\,,t)\;E}{(\theta+1)\;n(t)} - F_t = \frac{o\;A(j\,,\,t)\,cm_t\;\;E}{(\theta+1)\,(c^h\,n^h(t) + cm_t^l\,n^l(t) + cm_t^o\,n^o(t)} - F_t \tag{6}$$

1-4- The adoption decision:

A firm j^a maximizes the discounted value of total profits by choosing the adoption date *T*. Denoting the total profit function as $\Pi_{ja}(T)$ the optimization problem of this firm is as follow:

$$\Pi_{ja}(T) = \int_0^T e^{-rt}\,\pi_{ja}^o(t)\,dt + \int_T^{T+\tau} e^{-rt}\,\pi_{ja}^l(t)\,dt + \int_{T+\tau}^{+\infty} e^{-rt}\,\pi^h(t)\,dt - e^{-rT} Xa(T) \tag{7}$$

2-5- The firms entry decision

An entrant j^{el}, using the new technology, maximizes the discounted value of total profits by choosing the entry date T_{el}. Denoting the profit function as $\Pi_{j^{el}}(T_{el})$ the optimization problem of this entrant is as follows:

$$\Pi_{j^{el}}(T_{el}) = \int_{T_{el}}^{T_{el}+\tau} e^{-rt}\,\pi_{j^{el}}^l(t)\,dt + \int_{T_{el}+\tau}^{+\infty} e^{-rt}\,\pi^h(t)\,dt - e^{-rT_{el}}\;Xel(T_{el}) \tag{8}$$

2-9- The firms exit decision:

The exit decision is made prior to observing the next period's efficiency level and will involve a reservation rule:

$$h_j(t)\,v_j^l\,(t+1,\ c_j^l(t+1)\,)\ +\ (1\ -\ h_j(t)\,)\,v_j^o\,(t+1,\ c_j^l(t+1)\,)\ =\ S^o \tag{9}$$

where $h_j(t)$ is the probability of adopting of the new technology. A firm using the old technology will exit the industry the first time its rank rises above this reservation value $\hat{j}$.

2-10- Industry dynamics:

The composition of firms evolves in accordance with average probabilities of adoption *h*(t) (of o-firms), of technical success (*l*-firms) and of entry and exit (*o*, *l* and *h*-firms). Let $n^a(t)$ be the number of *o*-firms which adopt the new technology in period *t,* then

$$n^a(t)\ =\ h(t).n^o(t) \tag{10}$$

The number of *o*-firms, $no(t)$, evolves according to:

$$n^o(t+1)\ =\ n^o\ (t) - n^a(t)\ +ne^o\ (t)\ -\ ns^o\ (t) \tag{11}$$

$ns^o(t)$ is the number of exit among non innovating firms of type *o*, at the end of period *t* (or at the beginning of period *t*+1). $ne^o\ (t)$ is the number of firms which enter the industry at the end of period *t,* using the old technology. Let $ne^l(t)$ the number of innovating entrants of type *l* and $ns^l(t)$ the number of exits among *l*-firms. The total number of *l*-firms in period *t*+1 is:

$$n^l(t+1)\ =\ (1-\rho(t))n^l(t)\ \ +\ n^a(t)\ +\ ne^l(t)\ -\ ns^i(t) \tag{12}$$

The number of *h*-firms evolves according to:

$$n^h(t+1)\ =\ n^h(t)\ +\ \rho\ (t)\ n^l\ (t) \tag{13}$$

where $\rho(t)$ is the average probability of success of *l*-firms. Thus $\rho\ (t)\ \ n^l\ (t)$ is the number of *l*-firms, which have achieved, with success, their adoption and learning process and become high-efficiency firms.

Finally, the total number of firms operating in the industry in period *t,* $n(t)$, is:

$$n(t)\ =\ n^h(t)\ \ +\ \ n^l\ (t)\ \ +\ n^o(t) \tag{14}$$

This total number evolves in according to:

$$n(t+1) = n(t)\ +\ ne(t) - ns(t) \tag{15}$$

where $ns(t)$ is the total number of exits at the end of period *t* (or at the beginning of period *t*+1):

$$ns(t)\ =\ ns^h(t) + ns^l(t)\ +\ ns^o\ (t) \tag{16}$$

$ne(t)$ is the total number of entry at the end of period *t* (or at the beginning of period *t*+1):

$$ne(t) = ne^l(t) + ne^o\ (t) \tag{17}$$

FINDINGS AND CONCLUSION

Figures 1, 2-a, 2-b, 2-c and 3 present simulations of the endogenous variables* for different values given to the concentration degree ε , with $0 < \varepsilon < 2$. Before studying the contribution of these variables to industry efficiency growth, we begin by focusing on the effect of inter-firm efficiency variance on these technology, entry, exit and structure variables.

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*Further details on the resolution of the model may be obtained by contacting the author: Asma.Raies@malix.univ-paris1.f

Figure 2-a shows that inter-firm efficiency variance seems to inhibit entry, especially for non innovative *o*-firms (Acs and Audretsch, 1991). It shows that entry rate is high for low values of ε <0.5. The traditional industrial organization literature often implicitly assumed that there is insufficient entry in an imperfectly competitive market. By contrast, Mankiw and Whinston (1986) established a tendency toward excessive entry. We show that excessive entry is possible in an imperfectly competitive market when inter-firm variance in efficiency is low. However, mortality rates also tend to be high, resulting in high turbulence (Figure 2-b). Net entry, however, is much smaller than gross entry. This result confirms Beesly and Hamilton (1984) and Acs and Audretsch (1990, 1992), who show that most entrants are new, small firms that are far below any measure of minimum efficiency scale. In general, a large percentage of the entrants exit the industry within a few years after entry.

Comparing figures 2-a and 2-b, we can see the positive relationship between entry and exit for $0< \varepsilon <1.5$. More recent empirical studies on industry dynamics indicate high rates of turnover in terms of entry as well as exit of firms in many countries. Dunne et al. (1988), Dune and Roberts (1991) and Baldwin and Gorecki (1991) show that not only do entry and exit occur simultaneously but, very interestingly, they are positively correlated across industries at one point in time as well as over time within an industry.

Finally, comparing figures 1, 2-a and 2-b, we find that there is no absolutely monotonic relationship between entry and adoption, which means that high rates of innovation do not necessarily deter entry. However, the numbers of exit of (*o*-) and *l* –firms are positively correlated, respectively, with the average probabilities of adoption *h* and technical success ρ. This means that the probability of survival appears in sectors characterized by high rates of innovation

The results obtained from figure 3 show that less efficient *o*-firms achieve lower average efficiency than do (*l*-) and *h*-firms for each level of industry concentration and that the efficiency level of these firms is strictly decreasing in the concentration degree. We can see that efficiency growth for an industry as a whole, *cm* depends, to an important degree, on the distribution of efficiency among firms ε and not only on the firms' individual productivities. These results confirm those of the empirical work of Richard E Caves (1998).

There is no monotonic relationship between the average efficiency of the industry (*cm*) and the concentration degree ε . The effect of concentration is positive for moderate ($0.5 < \varepsilon < 1$) and very high values ($1.5 < \varepsilon < 2$) of this parameter, while it is negative for low ($0 < \varepsilon < 0.4$) and high values ($1 < \varepsilon < 1.5$). For this reason, we distinguish between these four intervals when analyzing the effect of inter-firm efficiency variance on the industry efficiency.

§- *Low concentration* ($0 < \varepsilon < 0.4$):

<u>*Technological effects:*</u> Figure 1 shows that in this interval, inter-firm efficiency variance does not affect the adoption rate, so the *adoption effect on industry average efficiency is zero*. In the same figure, parameter ρ seems to be very high (close to 1). This means that when inter-firm efficiency variance ε is very low, the average efficiency of *l*-firms is sufficiently close to that of high-efficiency firms (which is the best practice level *ch*). Thus, the likelihood of reaching this best practice level is very high for *l*-firms. However, we can see that this parameter decreases slowly in ε in this interval, which induces a *negative learning effect on the industry average efficiency.*

<u>*Entry effect:*</u> Figure 2-a shows that entry effect of less efficient *o*-firms is nil since *neo* = 0 for $0 < \varepsilon < 0.4$. The entry of innovative firms in this interval is excessive (see previous paragraph), but it is decreasing in this parameter which yields a *negative entry effect on average efficiency growth.*

<u>*Exit or selection effect:*</u> Figure 2-b indicates that concentration increases the exit number of less efficient *o*-firms (*nso*) which improves industry average efficiency (*cm*). However, concentration decreases the number of exiting *l*-firms, which has a negative effect on total efficiency. In this case, the *net selection effect on the industry is ambiguous.*

Structure effect: Figure 2-c shows that the total number of active firms (*n*) rises in inter-firm efficiency variance in the interval of [0 , 0.4]. This is due to an increase in the number of innovator firms (*n l*) and (*n h*) is also associated with a decrease in the less efficient *o*-firms (*n o*). This implies a *positive structure effect on aggregate efficiency* (*c m*). To sum up these results, we suggest that both *negative learning and entry effects dominate* the *positive structure effect* and thus provide a *decrease in industry average efficiency* (*cm*) in the degree of concentration for $\varepsilon \in [0, 0.4]$.

§- *Moderate concentration* (0,5 < ε < 1):

Technological effects: The adoption rate is increasing in the interval $[0.5, 1]$, yielding a *positive adoption effect* on average efficiency. However, the average probability of technical success is decreasing, which implies a *negative learning effect on industry efficiency*.
Entry effect is negative since entry of innovator *l*-firms (*nei*) is decreasing in ε and (*neo=0)*.
Exit or selection effect is positive since the number of firms exiting is higher for less efficient *o*-firms (*nso)* than innovative *l*-firms (*nsl*).
Structure effect is positive because the number of less efficient *o*-firms (*no*) remains lower than (*nl*) and (*nh*) in this interval.
We conclude from figure 3 that learning and entry effects are dominated by adoption, selection and structure effects, which induce a *positive net effect on industry average efficiency* (*cm*).

§- High concentration (1 < ε < 1.5) :

Technological effects: Both the *adoption and learning effects have a negative effect* on efficiency since the respective parameters *h* and ρ are decreasing in ε (figure 1).
Entry effect is nil since *nei = neo = 0* (fig 2-a).
Exit or selection effect is negative since ε lowers the exit number of less efficient firms (*nso*). The high survival rate of inefficient firms can be explained by the absence of entry of both low- and high-efficiency firms. We conclude that even if there is no direct effect of entry on efficiency, firm births and deaths are important contributions of competition to economic efficiency. Thus, market competition from new entrants indirectly raises firm efficiency in the industry (via selection effects).
Structure effect: One insight that emerges from figure 2-c is the persistence of less efficient *o*-firms for 1<ε <1.5. We can see that even the efficiency gap between high efficiency *h*-firms and low efficiency *o*-firms is large. However, we observe a significant persistence of less efficient *o*-firms. This persistence is due to low exit rates of firms in this interval. The existence of these inefficient firms that are suboptimal within the organization of an industry represents a loss in economic efficiency (Leonard Weiss 1991). We deduce the strong *negative structure effect* on aggregate efficiency.
As *all effects are negative*, the industry average efficiency decreases in $\varepsilon \in [1, 1.5]$

§- *Very high concentration* (1,5 < ε < 2) :

Technological effects: Both the *adoption and learning effects* have *a positive effect* on efficiency. Indeed, the respective parameters *h* and ρ are very high and increasing in ε (figure 1).
Entry effect is nil since *nei = neo = 0* (fig 2-a).
Exit or selection effect is strongly positive on efficiency. In facts the inter-firms efficiency variance is too high to produce a very excessive exit even for innovative (*l*-) and *h*-firms. The exit number of *o*-firms *nso* is very low because the majority of these firms has adopted the innovation and thus becomes of type *l* (fig 1) and there is no entry of *o*-firms (fig 2-a).
Structure effect: The strong selection effect seems to affect industry structure which tends to the monopolistic situation when ε tends to its maximal level. (We can see in table 1 that *n* = *nh* = *1* for $\varepsilon = 2$. This implies that the industry average efficiency tends toward the maximum level of efficiency *ch*. Thus the *Structure effect* is positive in this interval.
As *all effects are positive*, the industry average efficiency increases in $\varepsilon \in [1.5\ ,\ 2]$

An important conclusion of this sensitivity analysis is that the weight of each effect on aggregate change in efficiency is sensitive to the concentration level of the industry which we suppose exogenous in this paper. To sum up the results from this sensitivity analysis, we regroup these different effects in the subsequent table. We attribute the number 2 when the effect is dominant and explains the growth in efficiency, the number 1 for nil effects and 0 when effect is non dominant. The total gives the average explicative power of each effect.

Levels of Concentration / *efficiency effects*	*Low*	*moderate*	*high*	*very high*	*Total*
Adoption effect	1	2	2	2	**7**
Learning effect	2	0	2	2	6
Entry effect	2	0	1	1	**4**
Exit effect	1	2	2	2	**7**
Structure effect	0	2	2	2	**6**

The table suggests that adoption and selection effects play the more significant role in the changes in efficiency at the industry level. This means that the important sources of efficiency growth in the industry, over the four intervals, are the adoption of innovation by incumbents and the exit of very low efficiency plants. Learning and structure effects exerted the second most important influence on gains in industry efficiency. Finally the impact of firms entry didn't have a strong effect on average efficiency. These results accord with many empirical studies. For examle David L.Rigby and Jürgen Essletzbichler (1999) show that technological changes by incumbent plants outweighs the impacts of other influences on productivity and generate approximately 64% of the overall change in average productivity and that plant exit exerted the second most important influence on gains in industry efficiency. Finally the impact of plant entry didn't have a clear and significant effect on average efficiency

LIMITATION OF THE STUDIES AND FUTURE STUDIES

The framework developed in this paper formalizes a passive learning process and not firms' R&D behaviour, but seems to be flexible to include it. In order to investigate the effect of factors in explaining efficiency we have used, the simulations of the model in static contexts. In the future researches, these effects will be discussed in a dynamic context.

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Figure 1: The effect of efficiency variance on adoption and technical success

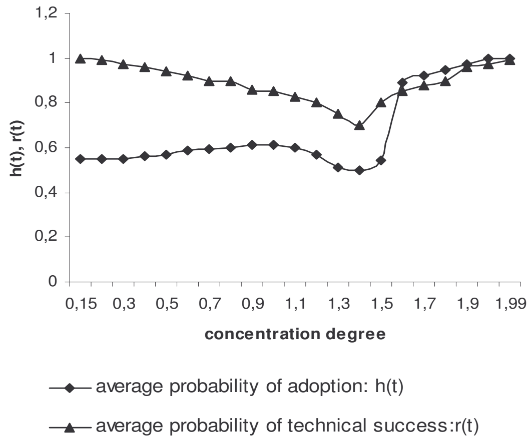


Figure 2-a: Effect of concentration on entry

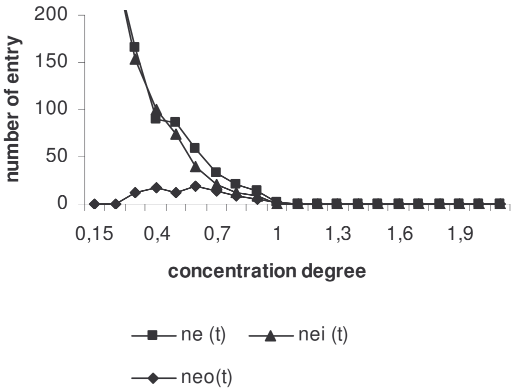


Figure 2-b: Effect of concentration on exit

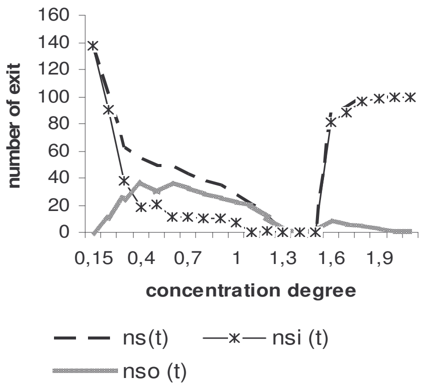
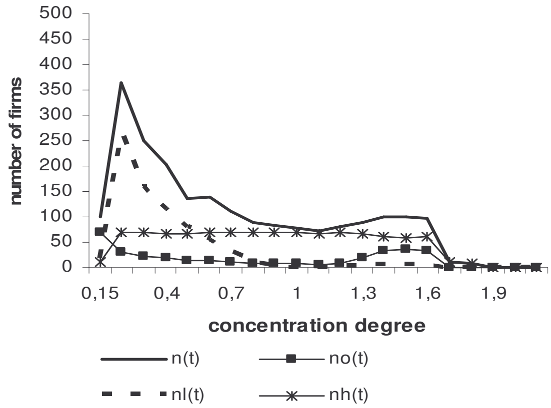


Figure 2-c: Effect of concentration on industry structure



APPENDIX

Figure 3: The effect of concentration degree on the average efficiencies

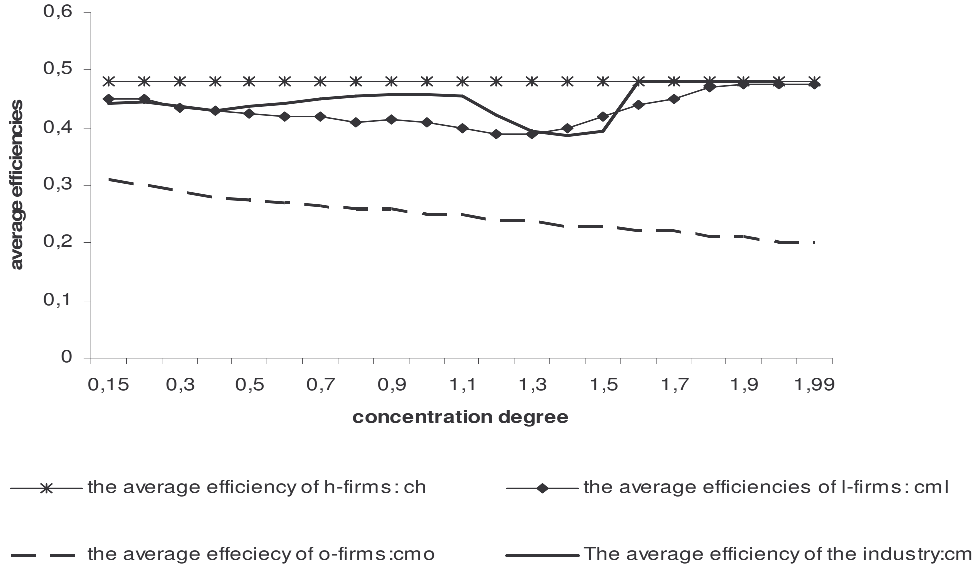


Table 1: Equilibrium value of endogenous variables for different levels of concentration degree ε

Concentration degree ε / Equilibruim values	*Low concentration*				*Moderate concentration*						*High. Concentration*					*Very High concentration*				
	0.1	*0.2*	*0.3*	*0.4*	*0.5*	*0.6*	*0.7*	*0.8*	*0.9*	*1*	*1.1*	*1.2*	*1.3*	*1..4*	*1.5*	*1..6*	*1.7*	*1.8*	*1..9*	*2*
<u>*Technological variables*</u>																				
h	0.55	0.5 5	0.55	0.55	0.56	0.57	0.58	0.59	0.6	0.61	0.61	0.6	0.57	0.51	0.5	0.54	0.89	0.92	0.95	0.98
ρ	0.99	0.99	0.97	0.97	0.96	0.94	0.92	0.9	0.9	0.86	0.85	0.83	0.8	0.75	0.7	0.98	0.85	0.80	0.90	0.97
<u>*Entry variables*</u>																				
n_e	400	250	166	118	87	59	33	20	13	1	0	0	0	0	0	0	0	0	0	0
n_{eo}	0	0	12	18	12	19	13	8	5	1	0	0	0	0	0	0	0	0	0	0
n_{el}	400	250	154	100	75	40	20	12	8	0	0	0	0	0	0	0	0	0	0	0
<u>*Exit variables*</u>																				
n_s	137	100	62	54	48	47	4	37	34	28	20	10	1	0	0	88	92	100	100	100
n_{so}	0	10	24	35	28	36	31	27	24	21	20	10	1	0	0	8	4	3	1	0
n_{si}	137	90	38	19	20	11	12	10	10	10	0	0	0	0	0	80	88	97	99	100
<u>*Structure variables*</u>																				
n	100	362	250	203	163	138	111	89	82	78	72	79	89	98	100	97	11	7	1	1
n_o	70	31	21	18	15	13	11	9	8	7	6	8	20	33	35	32	0	0	0	0
n_l	20	262	160	116	79	56	30	10	4	1	0	2	3	4	6	4	0	0	0	0
n_h	10	69	69	69	69	70	70	70	70	70	66	69	66	61	59	61	11	7	1	1
<u>*Efficiency variables*</u>																				
cmo	0.31	0.3	0.29	0.28	0.27	0.27	0.26	0.26	0.26	0.25	0.25	0.24	0.24	0.23	0.23	0.22	0.22	0.21	0.21	0.2
cml	0.45	0.45	0.43	0.43	0.42	0.42	0.42	0.41	0.41	0.41	0.4	0.39	0.39	0.4	0.42	0.44	0.45	0.47	0.47	0.48
ch	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48
cm	0.44	0.44	0.43	0.43	0.43	0.44	0.45	0.45	0.46	0.46	0.45	0.42	0.39	0.39	0.39	0.48	0.48	0.48	0.48	0.48