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Project no. 506022

Project acronym KEINS

KNOWLEDGE-BASED ENTREPRENEURSHIP:
INNOVATION, NETWORKS AND SYSTEMS

SPECIFIC TARGETED RESEARCH OR INNOVATION PROJECT

PRIORITY 7

Deliverable 24

**ARE THE DYNAMICS OF KNOWLEDGE-BASED
INDUSTRIES ANY DIFFERENT?**

Start date of project: 01-09-2004

Duration: 42 Months

CISEP

Final Paper

Project co-funded by the European Commission within the Sixth Framework Programme (2002-2006)		
Dissemination Level		
PU	Public	YES
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (including the Commission Services)	

ARE THE DYNAMICS OF KNOWLEDGE-BASED INDUSTRIES ANY DIFFERENT?

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Financial support from the European Commission (FP6) Project: «KEINS - Knowledge-Based Entrepreneurship: Innovation, Networks and Systems», Contract No.: CT2-CT-2004-506022 is gratefully acknowledged. The authors would also like to thank Camilla Lenzi, Fabio Montobbio, and the other participants at KEINS academic events for their helpful comments and suggestions.

1. Introduction

The concept of «knowledge-based industries» has been widely used both in academic circles and in policy-making over the last decade. The OECD (1999) has defined such industries as ones which are relatively intensive in their inputs of technology and/or human capital. This definition includes not only those manufacturing industries that are found to be highly dependent on R&D inputs, but also a number of service activities that are intensive users of high technology and/or have the relatively highly skilled workforce required to fully benefit from technological innovation (ibidem).

Knowledge-based industries (henceforth KBIs), thus defined, have been shown to play an increasing role in contemporary advanced economies. Between the mid-1980s and the mid-1990s, the contribution of these industries to the business value added of the advanced economies grew from around 45% to more than 50% (OECD, 1999). After a downturn at the beginning of the millennium (e.g. the share of high- and medium-high-technology manufacturing fell to about 7.5% of total OECD value added in 2002, compared to about 8.5% in 2000), the relative importance of KBIs in value added, international trade, and GDP growth has since shown clear signs of recovery (OECD, 2005).

Such a secular rise in the relevance of KBIs has drawn the attention of an increasing number of scholars to the study of such industries. Qualitative and quantitative studies on activities such as ICT-related industries, pharmaceuticals, biotechnology and business services, among others, have proliferated in recent decades. While the detailed study of specific KBIs has certainly contributed to a better understanding of each industry – and has often provided crucial insights that could be generalised to different contexts – it is, however, not clear to what extent the «knowledge-based» category is actually useful if one is concerned with understanding the evolution of firms and industries. Put differently, while there are strong reasons to draw the attention of academics and policy-makers to those industries which are heavily based on knowledge inputs, it is sensible to ask whether the dynamics of KBIs significantly differ from the dynamics of other industries.

There might be at least three different reasons for expecting KBIs to have a different behavioural pattern than the one found in other industries: demand directed to KBIs grows faster; these industries tend to be younger in terms of their industry and technology life-cycles; and they may face different sets of entry and exit barriers, particularly with regard to the need to invest in specialized knowledge assets.

As is well known, the empirical evidence drawn from several studies on industry dynamics has enabled the identification of some statistical regularities, which are often taken as stylised facts/stylised results on how firms and industries evolve over time (for surveys see Caves, 1998; Dosi et al., 1997; Geroski, 1995). Such statistical regularities include the following: the entry and exit of firms are both frequent phenomena, implying high levels of firm turnover in most industries; a high number of new firms leave the market shortly after entry; firm entry and exit are very often correlated, frequently being associated with similar determinants; entering and exiting firms are typically smaller than the average incumbent (which means that the impact of entry and exit on worker turnover tends to be lower than the impact on firm turnover); both the size and the age of firms have a positive impact on their survival chances, and usually a negative impact on growth.

In this paper, we intend to discuss the extent to which KBIs differ from other industries in relation to some of the stylised facts and regularities of industry dynamics that have just been mentioned. In particular, we analyse the patterns and the determinants of firm entry and post-entry performance (measured in terms of the survival of new firms), comparing groups of KBIs with the remaining industries and using data for the Portuguese economy in the second half of the 1990s.

The paper is organised as follows: in the following section, we present the data sources and propose our own classification for KBIs (an alternative to the one used by the OECD); the third section includes some relevant statistics on the entry and survival of new firms; in section 4, the models used in the paper are described; section 5 presents results for industry entry rates and section 6 deals with the determinants of new-firm survival; finally, section 7 concludes.

2. Data and the classification of KBIs

The study presented in this paper uses two main sources of data. The first one is the «Quadros de Pessoal» (QP henceforth) database, which compiles information on employers and employees collected on a yearly basis by the Portuguese Ministry of Employment and Social Solidarity (MTSS). The survey that supports this database was first carried out in 1982 (at present, the data available for research covers the period 1985-2005) and annual reporting to this survey is compulsory for all firms employing paid labour in Portugal. The survey includes questions related to the characteristics of both firms (e.g. total employment, industry classification, location, legal status, ownership, number of plants, etc.) and their employees (gender, date of birth, educational background, professional category, type of contract, etc.).

Both firms and workers are identified by their social security numbers, which in principle should make it possible to follow them over time. This feature of the QP database makes it an extremely valuable source of data for conducting analysis of both industry dynamics (see, for example, Cabral and Mata, 2003) and labour market dynamics (e.g. Portugal and Cardoso, 2006). In practice, however, some problems may arise in the use of these data for the purposes of longitudinal analysis. On the one hand, data on workers' characteristics were not collected either in 1990 or in 2001, restricting the availability of continuous series to the periods 1985-1989, 1991-2000 and 2002-2005. On the other hand, there was a change in the industry classification system from 1994 to 1995, which means that one cannot build continuous series of data on industries without making some rather arbitrary assumptions. Therefore, in this paper, we will restrict our use of data from the QP database to the period 1995-2000.

In order to enrich the information available at the industry level (namely, by adding information on revenues and costs, which is absent from the QP dataset), we also draw on the «Inquérito às Empresas Harmonizado» (IEH), an annual survey conducted by the Portuguese National Statistical Office (INE). The IEH dataset includes information on all firms with 100 or more employees and on a representative sample of firms with less than 100 employees belonging to all industries, with the following exceptions: financial

intermediation (ISIC classes 65 to 67); public administration and defence, and compulsory social security (ISIC class 75); private households with employed persons (ISIC class 95); and extra-territorial organizations and bodies (ISIC class 99).

A second group of industries was further excluded from our study, due either to data quality problems in the QP dataset or to our decision to focus our analysis on essentially market-oriented activities. This second group includes: agriculture, hunting and forestry (ISIC classes 1 and 2); fishing (ISIC class 5); mining and quarrying (ISIC classes 10 to 14); electricity, gas and water supply (ISIC class 40); education services (ISIC class 80), except driving schools and professional training; health services (ISIC class 80), except dental practice, clinical tests, and veterinary activities; sewage and refuse disposal, sanitation and similar activities (ISIC class 90); activities of membership organizations (ISIC class 91); recreational, cultural and sporting activities (ISIC class 92), except motion picture and video production, distribution, and projection; other service activities (ISIC class 93), except washing and (dry-)cleaning of textile and fur products, hairdressing and other beauty treatment, and funeral and related activities.

The list of industries that were retained includes 337 classes of an ISIC rev.3-equivalent classification system disaggregated to 5 digits, comprising 386,510 firms (166,604 of which entered the market between 1995 and 2000).

Since our final aim is to compare the dynamics of KBIs and those of other industries, we need to establish some criteria for what we understand as «knowledge-based». Besides considering the OECD's criteria for identifying KBIs (which includes both high-technology and medium-high-technology manufacturing industries, together with knowledge-based services), we have put forward an alternative classification of KBIs (KBI-MMG, which we will compare with KBI-OECD), taking advantage of the information available in the QP database on the employees' educational background. Thus, according to the KBI-MMG classification, an industry is considered to be a KBI if it is among the 10% of industries with the highest average proportion of employees holding a university degree (in the period 1995-2000).

The use of this alternative criterion for the classification of KBIs is beneficial in at least two senses: firstly, while the criteria used by the OECD to classify the knowledge intensity of manufacturing and service industries is based on information drawn from several countries over different periods of time, our classification was built on information about the firms which are actually under analysis, during the same period of observation; secondly, since the concept of «knowledge-basedness» is far from being an established one, the use of two different classification systems allows us to assess the extent to which the (dis)similarities between the dynamics of KBIs and those of other industries depend on the way in which we define the former.

In table 1 we can see that the two ways of classifying KBIs – the one used by the OECD and our KBI-MMG – overlap only partially.

Table 1 – Number of industries (at the 5-digit level) in different categories

		MMG classification		
		KBIs	Other industries	Total
OECD classification	KBIs	15	29	44
	Other industries	19	274	293
	Total	34	303	337

3. Descriptive statistics on entry, growth and survival

A simple inspection of some basic descriptive statistics on firms and industries allows us to detect a number of similarities and differences between the dynamics of KBIs and other industries.

Table 2 - Annual average industry statistics (1995-2000)

		All	KBI-OECD	KBI-MMG
Entry rate	Mean	0.11	0.11	0.16
	Coeff. Var.	0.55	0.64	0.44
Exit rate	Mean	0.08	0.07	0.08
	Coeff. Var.	0.50	0.57	0.38
Growth rate	Mean	0.05	0.08	0.11
	Coeff. Var.	2.60	1.63	2.27
Hirschman-Herfindhal Index	Mean	468	714	762
	Coeff. Var.	1.60	0.99	1.68
Median firm size	Mean	6.96	9.68	6.24
	Coeff. Var.	1.16	1.15	1.72
Price-cost margin	Mean	0.12	0.16	0.16
	Coeff. Var.	1.00	0.81	0.94
Advertising intensity	Mean	0.01	0.01	0.02
	Coeff. Var.	2.00	2.00	1.50
Proportion of graduates	Mean	0.06	0.14	0.25
	Coeff. Var.	1.33	0.86	0.40

Note: The data of the variables in this table is derived from the *Quadros de Pessoal* database, with the exception of the 'Price-cost margin' and 'Advertising intensity' variables, which were calculated with IHE-INE data.

The values displayed in table 2 are the industry annual averages of the corresponding variable for the period 1995-2000. The variables are defined as follows:

- the *entry rate* in year t is the ratio of the number of firms that were created at t to the total number of incumbents in the same year;
- the *exit rate* is the ratio of the number of firms that ceased to exist after t to the total number of incumbents in that year;
- the *growth rate* is measured in terms of the relative change in the total number of employees in an industry since the previous year¹;
- the *Hirschman-Herfindhal concentration index* is, as usual, the sum of squares of the market shares of every firm in each industry, with the market share of firm i being measured here as the proportion of employees working for i in relation to the total number of employees in the industry;

¹ The available data does not allow for the use of any other proxy for industry growth at the level of sectoral disaggregation that we are working with.

- the *median firm size* refers to the distribution of firm sizes in terms of the number of employees;
- the *price-cost margin* consists of the average industry ratio $(R-C)/C$ (where R represents total revenues and C total costs, in both cases for all firms) weighted by firm size;
- the *advertising intensity* is the industry average of the ratio of each firm's total spending on advertising to its total revenues, weighted by firm size; and
- the *proportion of graduates* is measured as the industry average proportion of employees in each firm who hold a university degree, weighted by firm size.

From the table above, it is worth emphasising the following aspects:

- (i) according to some dimensions, during the period under analysis, KBIs, regardless of the way in which they are defined, seem to behave in a fashion which is markedly different from the remaining industries – this is particularly so in the case of the growth rate, the price-cost margin, and the proportion of graduates; while the latter is essentially a result of the way industries are classified, the fact that, on average, KBIs grew faster and had higher price-cost margins during this period, confirms the idea that these industries contributed strongly to growth and value added;
- (ii) in some other aspects, the behaviour of the KBI-OECD group is not the same as the behaviour of the KBI-MMG group; in particular, the latter group shows higher entry rates (while the entry rate of KBI-OECD industries is not distinct from the entry rates of all sectors together) and lower median sizes (while the OECD's KBIs seem to be composed of firms which are bigger than the average);²
- (iii) finally, as far as the coefficients of variation are concerned, the information displayed suggests that there may be non-negligible differences between industries belonging to the same group of KBIs;

² The main reason for these differences lies in the fact that the proportion of service industries (which, typically, have higher entry rates and lower median firm sizes) is higher in the KBI-MMG group than in the KBI-OECD group.

this is particularly true in the case of the industries' growth rate, median firm size and advertising intensity (suggesting that industries which are considered as KBIs according to certain criteria may be quite distinct in many respects).

Beyond these particularities, table 2 confirms the idea that entry and exit are fairly pervasive phenomena in all sorts of industries. Furthermore, the inspection of correlations between entry rates and exit rates (Table 3) confirms that these two phenomena are not only pervasive, but also positively correlated – confirming what many studies of industry dynamics have already shown.

Table 3 - Correlation between industry entry and exit rates

	All	KBI-OECD	KBI-MMG
Pearson correlation	0.632**	0.738**	0.485**

** Correlation is significant at the 0.01 level (2-tailed).

In keeping with the stylised facts of industry dynamics, it can be seen that across all the groups of industries that we are analysing firms tend to enter with relatively small sizes and then to grow after entry (if they survive), typically at decreasing rates.

Table 4 shows, for different entry cohorts in each of the groups of industries under consideration, how the average size of new firms changes as they grow older.

Table 4 - Average dimension of firms per age for each entry cohort

	Year of entry	Firms' age						Total No. of firms
		1	2	3	4	5	6	
All industries	1995	4.0	4.7	5.3	6.0	6.7	7.5	21,410
	1996	4.0	4.8	5.3	5.9	6.4	.	21,582
	1997	3.9	4.8	5.7	6.4	.	.	24,892
	1998	3.9	4.8	5.6	.	.	.	27,990
	1999	3.7	4.6	29,573
	2000	3.9	41,157
	Total	3.9	4.7	5.5	6.1	6.6	7.5	166,604
KBI-OECD	1995	3.7	4.4	6.0	7.8	9.9	14.1	1,750
	1996	3.9	4.9	5.7	6.0	6.7	.	1,743
	1997	4.4	5.9	6.7	7.4	.	.	2,055
	1998	5.0	7.2	8.6	.	.	.	2,299
	1999	4.7	6.0	2,389
	2000	6.2	3,508
	Total	4.9	5.8	6.9	7.1	8.3	14.1	13,744
KBI-MMG	1995	3.0	3.6	4.2	4.9	5.3	5.7	1,964
	1996	3.3	4.0	4.4	5.0	5.5	.	2,066
	1997	3.8	4.9	5.4	6.5	.	.	2,413
	1998	4.6	5.6	6.9	.	.	.	2,713
	1999	3.9	4.9	3,008
	2000	6.3	4,617
	Total	4.5	4.7	5.4	5.5	5.4	5.7	16,781

Table 4 suggests that firms in knowledge-based industries tend to enter the market with higher sizes than firms in other industries. It also suggests that the individual firms in the KBI-MMG group that entered the respective industries grew more slowly than the rest of the firms during the period under analysis, particularly those in the KBI-OECD group.

Finally, further differences between KBIs and other industries can be detected by analysing the patterns of new-firm survival. Table 5 shows the percentage of firms per number of years of duration, again for different entry cohorts in each of the groups of industries under analysis.

Table 5 - Percentage of firms per number of years of duration for each entry cohort

	Year of entry	Firms' duration (No. of years)						Censored*	Total
		1	2	3	4	5	6		
All industries	1995	18.4	9.7	7.7	6.2	5.5	6.1	46.4	100.0
	1996	17.3	9.4	8.1	7.1	7.7		50.4	100.0
	1997	17.4	9.8	8.8	9.5			54.5	100.0
	1998	16.6	11.0	11.8				60.6	100.0
	1999	18.7	14.4					66.9	100.0
	2000	22.6						77.4	100.0
	Total	18.9	12.1	7.6	4.9	3.0	1.7	51.8	100.0
KBI-OECD	1995	14.3	8.4	6.7	5.6	6.0	5.3	53.7	100.0
	1996	13.0	7.9	6.7	6.5	7.0		58.9	100.0
	1997	13.7	8.1	7.2	6.7			64.3	100.0
	1998	10.7	8.5	9.4				71.4	100.0
	1999	15.0	9.4					75.6	100.0
	2000	18.4						81.6	100.0
	Total	14.6	9.8	6.6	4.3	3.0	1.5	60.2	100.0
KBI-MMG	1995	14.6	8.0	6.5	5.9	5.4	5.9	53.7	100.0
	1996	13.3	7.8	7.2	6.9	7.1		57.7	100.0
	1997	14.6	7.6	7.1	6.8			63.9	100.0
	1998	11.4	8.3	9.5				70.8	100.0
	1999	14.9	9.5					75.6	100.0
	2000	17.8						82.2	100.0
	Total	14.9	9.9	6.5	4.2	2.7	1.5	60.3	100.0

* The observations relating to the duration of firms are considered as censored when a firm was still active after the end of the period under consideration (i.e. 2000). We use the files related to 2001 and 2002 to check for censoring.

Table 5 clearly shows that firms in KBIs tend to survive longer than the average: while 31% of all firms that entered the market between 1995 and 2000 exited after the first two years, less than 25% of the firms in either of the two KBI groups did so; similarly, almost 2/3 of KBI firms survived after the fourth year, while the survival rate for the whole set of firms is about 56.5%.

To summarize, the descriptive statistics discussed above suggest that the dynamic behaviour of Portuguese knowledge-based firms and industries presented some distinctive features during the second half of the 1990s. In particular, it was shown that KBIs have grown faster, their price-cost margin has been higher, and firms within these industries have survived longer than the average. On the other hand, there seem to be some differences between the two KBI groups, namely in terms of entry rates.

In the following sections, we seek to understand to what extent such patterns are caused by the different general conditions and characteristics of the firms/industries that are included in each group or, alternatively, by differences in the factors that determine firm entry and firm survival in each industry type.

4. Theoretical considerations on panel data and survival models

The available data are organised in two dimensions – a time dimension and a cross-sectional dimension – which is the typical framework of panel data models. These two sources of variation will allow us to disentangle more accurately the effects of selected variables on industry entry. Consider the following benchmark model:

$$y_{it} = \mathbf{X}_{it}\beta + \varepsilon_{it} \quad \text{where } \varepsilon_{it} = \alpha_i + \gamma_t + \eta_{it} \quad (1)$$

The subscripts refer to the individual – i – and to time – t . The dependent variable will be either the industry entry rate or the firm growth rate. X stands for a $(1 \times k)$ vector of explanatory variables and ε is the disturbance term. This model is also known as an error components model³ due to its underlying error structure – it comprises three distinct variables, all of which are i.i.d. with mean 0, but with different variances, namely σ_α^2 , σ_γ^2 and σ_η^2 . We assume that the error term is uncorrelated with the regressors and that each of the first two components will model unobserved effects that are either specific to individuals or time. The final component is a purely random error. This specification neatly accommodates the possible presence of individual autocorrelation.

The model for the determinants of entry rates will be estimated by maximum likelihood. Our preference for a random effects model over a fixed effects one depends mainly on a twofold argument. Firstly, we want to consider time-invariant variables as regressors and only a random effects specification allows us to estimate parameters associated with those variables. Secondly, our dataset is rather lengthy in cross-sectional terms but short in terms of its time dimension. Estimating a fixed effects model under such circumstances would

³ Or random effects model.

drastically decrease the degrees of freedom. Nevertheless, our specification will be tested against other standard models.

There is still one important issue to be discussed concerning the data panel models applied to the analysis of entry determinants. In these models, the entry rate will be the dependent variable. By definition, the entry rate is constrained to lie between 0 and 1. This fact alone implies inherent heteroskedasticity of the model. However, the severity of this problem is not very great. For the sake of simplicity a linear model is preferred although the model may predict entry rates outside the (0,1) interval⁴.

While the study of entry is based here on data panel models, the determinants of new-firm survival are investigated using a piecewise-constant exponential hazard model, a semi-parametric type of approach to the statistical analysis of duration data (Jenkins, 2005; Lancaster, 1990).

A central concept in this type of analysis is the *hazard function*. In the present context, the hazard function corresponds to the instantaneous probability of a firm exiting the industry at time t , given that it actually stayed in the market until t . Formally,

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{P(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t} = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)},$$

where $f(t)$ is the probability density function, $F(t)$ is the distribution function, $S(t)$ is the survival function (i.e. the probability that a firm will survive after t).

One model that has often been used in this context is the Proportional Hazards (PH) model. Such a framework is characterised by the fact that it satisfies a separability assumption:

$$(2) \quad h(t; X) = h_0(t) e^{X\beta}$$

⁴ We tested for this possibility and, in all our models, it occurred in only 0.5% of cases.

where $h_0(t)$ is a 'baseline hazard' function which depends on t and $e^{X\beta}$ is an individual specific non-negative function of covariates X , which does not depend on t . This property greatly simplifies the estimation of the model; it implies that: (i) the pattern of 'duration dependence' is monotonic and common to all firms (i.e. the probability of survival is monotonically increasing or monotonically decreasing); and (ii) the role of firms' characteristics and other covariates (such as industry characteristics or macroeconomic conditions) is to scale up or down the survival-duration profile.

The basic idea underlying the piecewise-constant hazard model, which we will be using below, is the following. The time axis is partitioned into a number of intervals using cut-points (which are chosen by the researcher – in the present case, each interval corresponds to one year), and it is assumed that the baseline hazard is constant within each interval, although it may differ between intervals. The hazard function therefore becomes:

$$(3) \quad h(t; X) = \begin{cases} h_1 e^{X_1 \beta} & 0 < t \leq c_1 \\ h_2 e^{X_2 \beta} & c_1 < t \leq c_2 \\ \dots & \dots \\ h_K e^{X_K \beta} & c_{K-1} < t \end{cases}$$

where the time axis is divided into K intervals by points c_1, c_2, \dots, c_{K-1} . Besides the already mentioned flexibility concerning the shape of the hazard function (note that there will be one baseline hazard for each interval), this specification provides a relatively simple way of incorporating time-varying covariates – a relevant feature in the context of the present paper, where we have data for the same variables for successive years.

Regarding the likelihood function, it is worth noting that we are dealing with annual data. This means that we do not know the exact time t at which firms exit the market; we only know the year interval in which exit (or censoring) occurs. Let $\{c_k\}$ represent, as before, the end points of the K intervals into

which the data is grouped (with $c_0=0$ and $c_K=\infty$).⁵ Thus, the individual contribution to the likelihood function will be:

$$(4) \quad L_i = [f(c_k)^{\delta_i} \cdot S(c_{k-1})^{1-\delta_i}]^{d_{ik}},$$

with

$$\begin{cases} d_{ik} = 1 & \text{if firm } i \text{'s exit or censoring happen in the interval }]c_{k-1}, c_k] \\ d_{ik} = 0 & \text{otherwise} \end{cases}$$

and

$$\begin{cases} \delta_i = 1 & \text{if firm } i \text{ exits in the interval }]c_{k-1}, c_k] \\ \delta_i = 0 & \text{if firm } i \text{ is censored in the interval }]c_{k-1}, c_k] \end{cases},$$

Noting that $f(c_i)$, the probability of firm i exiting during the interval, corresponds to

$$f(c_k) = \Pr(c_{k-1} \leq T < c_k) = S(c_{k-1}) - S(c_k),$$

each firm's contribution to the likelihood function becomes

$$(6) \quad L_i = \left\{ [S(c_{k_i-1}) - S(c_{k_i})]^{\delta_i} \cdot S(c_{k_i-1})^{1-\delta_i} \right\}^{d_i} = \left\{ \left[1 - \frac{S(c_{k_i})}{S(c_{k_i-1})} \right]^{\delta_i} \cdot S(c_{k_i-1}) \right\}^{d_i}$$

It is possible to show (see Lancaster 1990, pp. 176-181) that the elements of equation (6) above can be expressed in terms of the hazard function presented in (5) as follows:

$$\frac{S(c_{k_i})}{S(c_{k_i-1})} = \begin{cases} \exp\{-h_k e^{X_k \beta} (c_k - c_{k-1})\} & \text{if } k = 1, 2, \dots, K-1 \\ 0 & \text{if } k = K \end{cases}$$

$$S(c_{k_i-1}) = \exp\left\{-\sum_{l=1}^{k-1} h_l e^{X_l \beta} (c_l - c_{l-1})\right\}, \quad k = 2, \dots, K$$

⁵ In the present case, the intervals that determine the baseline hazards basically coincide with the intervals into which the data is originally grouped. This, however, is not necessarily the case in this type of application.

5. Determinants of industry entry rates

In order to analyse the determinants of entry, we use a model inspired by the seminal paper by Orr (1974). In general terms, we assume that the entry of new firms into a market is influenced by three groups of factors: incentives to entry, entry barriers and the behaviour adopted by incumbents in order to prevent entry. Both datasets available for the purpose of this study allow us to build approximate indicators for each of those groups of factors. Thus, the following explanatory variables were used in the regressions⁶:

- *Price-cost margin*: this is considered as an incentive to entry, being used as a proxy for expected profitability. We expect it to have a positive effect (if any) on entry rates.
- *Industry growth*: this is used as another proxy for expected profitability. We expect it to have a positive effect on entry rates.
- *Median firm size*: this is used as a proxy for scale economies. It is expected to have a negative effect on entry rates, since firms must enter with larger sizes if they are to avoid incurring higher average costs. The barrier to entry stems from the need to raise more capital for start-up purposes, given imperfections in the capital markets.
- *Advertising intensity*: this is used as a proxy for product differentiation. It is expected to have a negative effect on entry rates, since new firms must incur additional advertising costs or lower revenues when entering the market.
- *Hirschman-Herfindhal (HH) index*: higher concentration levels are expected to facilitate collusion among the incumbents. This will make the entry of new firms harder.

The dependent variable in the regressions is the entry rate at the 5-digit industry level, computed as the proportion of incumbent firms in each industry at period t which have entered the market in that same period. Table 7 shows the bivariate correlations between the variables used in our regressions:

⁶ See section 3 above for a description of these variables.

Table 7 – Pearson indexes of the bivariate correlations between the determinants of industry entry rates

	Price-cost margin	Industry growth	Median firm size	Advertising intensity	HH index
Entry rate	.056(*)	.437(**)	-.367(**)	.007	-.090(**)
Price-cost margin		.097(**)	.037	-.060(*)	.050(*)
Industry growth			-.157(**)	.044	-.014
Median firm size				.002	.118(**)
Advertising intensity					.149(**)

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

Table 7 shows that the price-cost margin, the industry growth rate, the median size of firms per industry and the HH index are all significantly correlated with the industry entry rate, with the expected signs; on the contrary, the bivariate correlation between entry rates and advertising intensity is non-significant. Although the PCM is admittedly a rather crude proxy for expected profitability, we can see that it is significantly and positively related with the rate of industry growth and the HH index (as is to be expected), and that it is significantly and negatively related to advertising intensity, possibly suggesting that intensive advertising is associated here with tougher competition (and, accordingly, with higher costs and/or lower revenues).

While many of the explanatory variables are significantly correlated between one another, the Pearson correlation indexes (in absolute values) are not sufficiently high to raise problems of multicollinearity in a multivariate regression context.

Table 8 shows the results of the regressions for the complete dataset of industries.

**Table 8 – Regression results for the determinants of industry entry rates
(all industries included)**

	1 (All industries)	2 (All industries)	3 (All industries)
Price-cost margin	.020882 **	.020480 **	.018573 **
Industry growth	.096306 **	.095980 **	.095321 **
Median firm size	-.002548 **	-.002569 **	-.002509 **
Advertising intensity	-.024738	-.025961	-.055734
Hirschman-Herfindhal index	-.000009 **	-.000009 **	-.000009 **
KBI-OECD		.004708	
KBI-MMG			.037608 **
Intercept	.128008 **	.127717 **	.124947 **
Sigma²	.002740 **	.002740 **	.002624 **
Schwarz B.I.C.	-3004.16	-3000.66	-3011.23
Log likelihood	3033.83	3034.04	3044.61
Number of observations	1685	1685	1685

** significant at 5%

In column 1, we can see that all explanatory variables have the expected impact on entry rates, although the parameter relating to the intensity of advertisement is not significant. It is worth noting that the individual (i.e. industry) effect is quite relevant, suggesting that, on average, there are particular features of each industry not captured by the explanatory variables used in the regression that play a relevant role in explaining the entry rates; this is evident when one compares the SBIC statistics of the chosen models with the statistics of models estimated by the plain ordinary least squares method or models estimated by the within-group estimator even after accounting for the yearly effects (usually associated with fixed effects models – see the results in the appendix).

In order to assess whether being a KBI can influence the level of the entry rate in each industry – after taking into account the five explanatory variables listed above – we include in regressions 2 and 3 a dummy variable for KBIs (in regression 2 we use the OECD classification, and in regression 3 our own classification). The results shown in table 8 indicate that, unlike the KBI-OECD group, the KBI-MMG group is positively and significantly associated with higher entry rates at the industry level (even when several determinants of entry are taken into account).

We are also interested in understanding the extent to which the determinants of entry differ for distinct groups of industries. More specifically, we want to analyse whether the factors that affect entry in KBIs are different from the ones that affect entry in general. For this purpose, we ran separate regressions for each group of KBIs using the same explanatory variables as before. The results of these regressions are shown in table 9.

Table 9 – Regression results for the determinants of industry entry rates (separate results for different groups of industries)

	1 (All industries)	4 (KBI-OECD)	5 (KBI-MMG)
Price-cost margin	.020882 **	.004539	-.003443
Industry growth	.096306 **	.065881 **	.058102 **
Median firm size	-.002548 **	-.001762 **	-.000195 **
Advertising intensity	-.024738	.070825	-.223831
Hirschman-Herfindhal index	-.000009 **	-.000021 **	-.000005
Intercept	.128008 **	.137150 **	.166514 **
Sigma²	.002740 **	.003798 **	.004201 **
Log likelihood	3033.83	385.383	268.016
Number of observations	1685	220	170

** significant at 5%

Regressions 4 and 5 show us that, contrary to the general case, the impact of the PCM was not significant as a determinant of entry rates within knowledge-based industries in Portugal during the period 1995-2000. On the other hand, the growth rate of industries and the median size of firms both affect entry rates in all types of industries, irrespective of their knowledge intensity. Finally, while the level of market concentration had only a rather small, although significant, effect on entry in the general case, its impact is non-significant in the case of the KBI-MMG group.

We will leave the discussion of these results for the concluding section of the paper. Before that, however, we will discuss the determinants of firm survival.

6. Determinants of new-firm survival

In the last two decades, there has been a proliferation of studies on the determinants of new-firm survival. Firm survival has been found to be robustly related with firm-specific variables such as size and age – which typically have a negative impact on survival chances (e.g. Dunne et al., 1989; Mata and Portugal, 1994; Audretsch and Mahmood, 1995; Wagner, 1999) – and less robustly related with other industry-specific and macroeconomic variables.

The specific relationship between survival and the age of firms which is identified in the empirical exercises can be very sensitive to the models used for estimations. As was pointed out in section 4 above, the Proportional Hazards (PH) model is often used in studies on the determinants of new-firm survival, largely due to the simplicity of its estimation. However, this model implicitly assumes that the pattern of ‘duration dependence’ is monotonic, i.e. that the probability of survival monotonically increases or monotonically decreases with a firm’s age – which need not be the case.

In fact, while there are reasons to believe that age makes firms less prone to failure – e.g. it may take time for firms to discover the true worth of their competencies (as suggested by Jovanovic, 1982) or to develop specific knowledge, trust and appropriate routines (as put forward by organisational ecologists; see Carroll and Hannan, 2000) – it is not obvious that this relationship has to be monotonic. In fact, it can be argued that new firms will stay in the market until such time as they have exhausted the initial resources that they gathered for the new venture. This may imply that the probability of survival will decrease in the years immediately after entry, and increase only after new firms have either succeeded in stabilising their cash-flows or, alternatively, exhausted their start-up financial resources and therefore exited the market. The model we use here, the piecewise-constant hazard model, does not impose any specific form on the relationship between survival and age, therefore allowing for the identification of possible non-monotonic shapes for such a relationship.

In addition to age and size, we have included as an explanatory variable the proportion of graduates (as a proxy for human capital). Furthermore, we have

controlled for the annual growth rate of the industry that each firm belongs to, as well as for the annual GDP growth (in order to account for the influences of the general economic climate upon firms' survival chances).

The tables below present the results of the regressions, with the hazard rate being used as the dependent variable (see section 4).

Table 10 – Regression results for the determinants of new firm hazards (all firms that entered between 1995 and 2000 are included)

	6 (all new firms)	7 (all new firms)	8 (all new firms)
Firm age = 6 years	1.10065 **	.544396 **	.446487 **
Firm age = 5 years	1.59327 **	.969400 **	.855364 **
Firm age = 4 years	1.76050 **	1.08398 **	.961047 **
Firm age = 3 years	1.70149 **	1.03472 **	.913830 **
Firm age = 2 years	1.61168 **	.964947 **	.848016 **
Firm age = 1 year	-.646441 **	-.614049 **	-.613525 **
Current Size	-.002843 **	-.002847 **	-.002809 **
Proportion of graduates	-.165898 **	-.020851	.027766
Industry growth	-.090384 **	-.090328 **	-.088400 **
GDP growth	-.698987 **	-.532830 **	-.501292 **
KBI-OECD		-.092620 **	
KBI-MMG			-.099781 **
Schwarz B.I.C.	163939	164697	165106
Log likelihood	-163879	-164631	-165039
Number of observations	166 604	166 604	166 604

** significant at 5%

Table 10 presents the regression results for the determinants of new firm hazards, considering all firms that entered the market between 1995 and 2000. The results of regressions 6 to 8 reveal that the relationship between survival and the age of firms is in fact non-monotonic: the hazard rates of firms increase from the first to the fourth year, and then decrease with age thereafter. In regression 6, all other determinants of firm survival have the expected impact – a firm's survival is positively (or the hazard rate is negatively) related with its size, its human capital endowment, the growth of

the industry that it belongs to and GDP growth – with all coefficients being statistically significant at a 5% level.

Introducing dummy variables in regressions 7 and 8 for the two KBI groups renders the human capital variable insignificant (while the coefficients of such dummies are both significant and have the expected sign). This fact can have two alternative explanations: either the proportion of graduates is in fact not important per se, only appearing to be significant in regression 6 due to the exclusion of what would be the 'true' determinant of firm survival (i.e. being or not a part of a KBI); or, alternatively, the fact that the inclusion of the KBI dummies renders the human capital coefficient statistically insignificant may just be a result of the non-negligible correlation between the latter variables and each of the KBI dummies.

One way to sort out this issue is to run separate regressions for different groups of firms, according to the type of industry that they are part of. Table 11 displays the results of such regressions.

Table 11 – Regression results for the determinants of new firm hazards (separate results for firms belonging to different groups of industries)

	6 (All new firms)	9 (New firms in KBI-OECD)	10 (New firms in KBI-MMG)
Firm age = 6 years	1.10065 **	3.42088 **	1.09060 **
Firm age = 5 years	1.59327 **	4.71319 **	1.71049 **
Firm age = 4 years	1.76050 **	4.87920 **	1.84687 **
Firm age = 3 years	1.70149 **	4.78600 **	1.77675 **
Firm age = 2 years	1.61168 **	4.51827 **	1.64271 **
Firm age = 1 year	-.646441 **	-.841141 **	-.820166 **
Current Size	-.002843 **	-.004981 **	-.002819 **
Proportion of graduates	-.165898 **	-.126927 **	-.086692 **
Industry growth	-.090384 **	-.187366 **	-.133616 **
GDP growth	-.698987 **	-1.65182 **	-.809479 **
Schwarz B.I.C.	163939	11148.0	13745.1
Log likelihood	-163879	-11100.3	-13696.5
Number of observations	166 604	13 744	16 781

** significant at 5%

Table 11 shows that the main results discussed for the general case (regression 6) remain essentially unchanged, regardless of the industry group under analysis (regressions 9 and 10): the hazard rates are non-monotonically related with age (increasing until the fourth year and decreasing thereafter) and negatively related with the size of firms, the proportion of graduates among the labour force and the growth rates of both the specific industry and the economy as a whole.

7. Conclusions

This paper has compared the dynamics of knowledge-based industries (KBIs) with the universe of all market-oriented industries in Portugal between 1995 and 2000. Our main goal was to discuss the extent to which KBIs differ from other industries in relation to some basic stylised facts and regularities (concerning firm entry, and post-entry growth and survival) which have been identified in a number of previous studies.

In our comparative exercise, we took two classifications of knowledge-based industries, the one put forward and used by the OECD (KBI-OECD) (OECD 1999) and another one, suggested by us (KBI-MMG), based on the proportion of graduate workers in each industry. The data analysed stems mainly from the Portuguese social security database («Quadros de Pessoal») based on an annual survey of all firms with paid workers, and was complemented with data on costs and revenues at the industry level from the INE, the national statistical office.

The descriptive analyses of the data have basically confirmed a number of well-known statistical regularities concerning the evolution of firms and industries, namely: entry and exit are quite pervasive in all sorts of industries; the firms' average size grows as they grow older; and the proportion of firms leaving the market in the first few years after entry is quite high.

In the same vein, the regression analyses have confirmed some stylised results, in particular:

- the entry of new firms responds positively to incentives (in particular to industry growth) and negatively to barriers to entry (namely, the presence of economies of scale measured in terms of the median firm size in each industry); and
- the survival of new firms is positively related with size, even after controlling for human capital endowment, industry growth, and GDP growth.

As far as the impact of age on firm survival is concerned, we found a non-monotonic relationship, with the hazard rates of firms increasing up to the fourth year after entry and declining thereafter. While this result deviates from the frequently found positive relationship between the age and survival of firms, this deviation may well be explained by the fact that many previous studies on firm survival did not allow for a non-monotonic relationship between the two variables.

More relevant to the aim of this paper is the discussion of the specificities of KBIs in the domains just mentioned. In fact, we found that KBIs (regardless of how they are classified) and the firms within them show some signs of distinctiveness in their dynamics in comparison with the general case. In particular, on average:

- KBIs have higher growth rates;
- entry within the KBI groups is less responsive to incentives (contrary to the general case, the impact of the PCM on entry is not significant; and the impact of industry growth, though significant, is less expressive);
- KBI firms have higher survival chances;
- the survival of firms belonging to KBIs is notably more dependent on industry growth than in the general case.

These results do much more than simply confirm the idea that knowledge-based industries were fast-growing industries in the second half of the 1990s. They seem to suggest that the creation of firms in these industries responds to incentives in a different way than in other industries, a result with potentially relevant policy implications. In particular, with the variables accounting for profitability expectations and entry rates not showing the same pattern as in the general case, incentive-based policies (e.g. tax incentives for new technology-based firms) might be less effective in promoting entrepreneurship in these industries than in other cases (in other words, the determinants of new-firm creation are probably more closely related with the availability of relevant skills and competences than with market incentives).

These results also seem to suggest that the survival of firms in knowledge-based industries is more susceptible to downturns in the business cycle, highlighting the need to pay greater attention to the sustainability of new knowledge-based enterprises when devising mechanisms for the support of such activities.

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A. Appendix

Table A1 – Pooled regression results (estimation by OLS)

	1 (All industries)	2 (All industries)	3 (All industries)
Price-cost margin	.017412	.016900	.007924
Industry growth	.133204 **	.132938 **	.123093 **
Median firm size	-.002440 **	-.002449 **	-.002401 **
Advertising intensity	.014832	.012862	-.104619
Hirschman-Herfindhal index	-.000005	-.000005	-.000006
KBI-OECD		.001557	
KBI-MMG			.039507 **
Intercept	.123856 **	.123832 **	.122829 **
Schwarz B.I.C.	-2527.40	-2523.76	-2563.69
Log likelihood	2549.69	2549.76	2589.70
Number of observations	1685	1685	1685

** significant at 5%

* significant at 10%

Table A2 – Fixed effects regression results (estimation by OLS)

	1 (All industries)	2 (All industries)	3 (All industries)
Price-cost margin	.027740	Estimation not possible due to variables being constant in time	Estimation not possible due to variables being constant in time
Industry growth	.025084		
Median firm size	-.003702 **		
Advertising intensity	-.137820		
Hirschman-Herfindhal index	-.000010		
KBI-OECD			
KBI-MMG			
Intercept	.123856 **		
Schwarz B.I.C.	-2284.25		
Log likelihood	3554.70		
Number of observations	1685		
F test of individual intercepts	9.179 ** ⁷		

** significant at 5%

* significant at 10%

⁷ The null is accepted at a 5% level, meaning that the individual intercepts are statistically significant.