Labour mobility and firm survival in knowledge intensive services

Ricardo Mamede

Daniel Mota

2012

WP n.º 2012/08

DOCUMENTO DE TRABALHO

WORKING PAPER

DINAMIA'CET
CENTRO DE ESTUDOS SOBRE A MUDANÇA SOCIOECONÓMICA E O TERRITÓRIO
ISCTE-IUL

FCT
Fundação para a Ciência e a Tecnologia
MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E ENSINO SUPERIOR

Labour mobility and firm survival in knowledge intensive services

Ricardo Mamede ♣

Daniel Mota♣♣

WP n.º 2012/08

♣ DINÂMIA'CET-IUL and ISCTE-IUL- Department of Political Economy.
♣♣ INE – Instituto Nacional de Estatística.

Labour mobility and firm survival in knowledge intensive services[1]

ABSTRACT:
In this paper we use a matched employer-employee dataset on knowledge-intensive business services in Portugal in order to analyse the impact of labour mobility on the survival chances of firms. On the basis of a piecewise-constant exponential hazard model, we test and do not reject the following hypotheses: (i) worker flows in excess of net job flows are negatively related with firms' survival chances; (ii) job match dissolutions are more deleterious to firms when they involve workers with high human capital; and, inversely, (iii) new hires are specially beneficial if they imply the firms' access to more skilled workers. These results add to the scarce statistical evidence on the impact of labour market dynamics on the evolution of firms and industries.

NOTE: The data used in this paper is subjected to privacy laws and its use has to be requested to the Portuguese Ministry of Employment and Social Solidarity. The TSP code is available from the authors.

JEL Codes: J63, L84

KEY WORDS: Labour mobility, Firm survival, Industry dynamics

[1] The research underlying the present paper was partly funded by the Portuguese Science and Technology Foundation (grant ref. SFRH/BD/8765/2002). The Portuguese Ministry of Employment and Social Solidarity has allowed the access to the data used in this paper. The support provided by these institutions is gratefully acknowledged.

1. INTRODUCTION

In many industries the performance of firms is strongly related with their ability to manage human capital. This is particularly true for industries that rely on a highly specialised labour force, and in which the growth of firms depends on their capacity to recruit skilled workers and to avoid poaching by competitors (see, for example, Baron 2004, on hi-tech firms, and Mamede 2002, for IT consultancy). In such contexts, at least, one can expect to observe a systematic relation between the patterns of worker turnover and the post-entry performance of firms and in particular their survival prospects.

In the last two decades the studies on the determinants of firm survival have proliferated. Firm survival has been found to be robustly related with firm-specific variables such as size and age (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. However, evidence on the relation between firm survival and labour mobility is rather scarce (Mamede, 2009). While it is possible to find occasional evidence on such a link in the existing literature – as in the studies of worker and job flows by Lane et al. (1996) – this is only enough to encourage further investigations about the way the inflows and outflows of heterogeneous workers may impact on the hazards of firms.

In this paper we use data collected by the Portuguese Ministry of Employment and Social Solidarity on 9.996 firms and 50.283 workers in knowledge-intensive business services (KIBS) industries (from 1991 to 2000), in order to analyse the impact of labour mobility on firm survival. KIBS industries are particularly well-suited to the analysis of such relation: they consist of companies that provide inputs to the business processes of other organisations, and which are heavily based on advanced technological or professional knowledge embedded in their employees (EMCC, 2005)[2]; furthermore, these are industries which have grown significantly in recent decades, with their pace of growth being often hampered by the availability of labour resources (Rubalcaba-Bermejo, 1999). As such they can be considered as the ultimate example of industries in which worker turnover is crucial for the performance and survival of firms.

[2] This includes firms that provide services in such domains as information technology consultancy, research and development, architecture and engineering, legal activities, accounting and auditing, market research, management consulting, and advertising, among others. See technical annex for a detailed presentation of the industries included in the analysis.

The paper is organised as follows. We start by discussing the theoretical issues underlying the hypotheses to be tested. Section 3 presents the data and some descriptive statistics, and section 4 refers the method used in the estimation. Section 5 presents and discusses the results, and section 6 concludes de paper.

2. THEORETICAL ISSUES AND HYPOTHESES

It has been noted for a long time that worker turnover has both positive and negative consequences for firms. In a paper that influenced many later developments in organisation studies, Staw (1980) discussed in detail the main costs and benefits of turnover to organisations. Those costs include: selection, recruitment and training costs (which are specially high for complex jobs in the context of tight labour markets, in particular for firms which cannot rely on dedicated departments and/or internal mobility); operational disruption (particularly when turnover affects central functions in the context of highly interdependent structures); and de-moralisation of organisational members (when turnover affects group cohesion). While the organisational costs of worker mobility are often emphasised, turnover may also be beneficial to the performance of organisations in several ways, such as: new hires can be associated with more motivated, more competent, and more educated workers; the exit of workers (in the form of either fires or quits) is one of the possible solutions to entrenched organisational conflict; worker turnover (both inwards and outwards) can lead to a diversification of the external links of organisations, with benefits in terms of access to various types of resources.

The idea that turnover can have deleterious consequences (which, to some extent, are anticipated by firms and reflected in their personnel policies) has provided the basis for the explaining labour market related phenomena. For example, efficiency wage theories (Akerloff and Yellen, 1986) incorporate the idea that employee turnover is reduced by increasing current and (expected) future wages and other benefits. In cases when reducing turnover rates is beneficial to the firm (e.g., increasing productivity by promoting investments in firm-specific capital, and/or reducing the costs of searching and recruitment), that idea explains why wages are often higher than expected, or why incentive regimes are particularly generous in rewarding tenure (as found, for example, by Møen, 2005, in the case of technical staff in R&D-intensive firms, where the wage-tenure profile is particularly steep).

The fact that firms respond to the risks posed by employee turnover resorting to internal incentive systems may suggest that, ultimately, the mobility of workers is rendered irrelevant (in the sense that the levels of turnover would result from firms' optimal choices). While it has been shown that firms are characterised by a persistent and heterogeneous propensity for turnover (e.g., Burgess et al., 2000; Lane et al., 1996), one could explain such heterogeneity by arguing that firms chose different optimal levels of turnover because the relevant factors underlying the optimal choice of personnel policy mix differ form firm to firm – and have little to do with persistent differences in firms' ability to avoid the costs of turnover.

However, preliminary results on the relation between worker turnover and firm survival seem to suggest otherwise. In their study of churning flows (understood as the flows of workers in and out of firms in excess of what would be necessary to accommodate net changes in total employment), Lane et al. (1996) have used a hazard rate model in order to test the prediction that high churning firms will have lower survival rates; the results obtained strongly support that prediction. Although using alternative estimation methods, Burgess et al. (2000) have reached similar conclusions concerning the relation between job churning and firm survival. These results reinforce the argument that worker turnover may not be optimising for firms, specially in those cases in which the proportion of employees that either enter or leave a firm is much higher than what would be necessary to accommodate net employment changes associated with the expansion/contraction of firms (or, to use the expression put forward by Lane et al., 1996, when churning is high).

The arguments presented above suggest a number of ways in which labour mobility can be related to firm survival, and which can guide empirical investigations of the subject. As is often the case, some of the variables establishing that causal link may be hard to measure directly on the basis of the data available in the present context (for example, the direct costs of selection, recruitment, and training; the potential for organisational disruption or conflict resolution; or the establishment of relevant external links). Still, we can expected to identify the following relations on the basis of the available data: (i) churning rates will be negatively related with firms' survival chances; (ii) job match dissolutions will be more deleterious to firms when they involve workers with high human capital (using, e.g., educational attainment as a proxy), rather than low human capital; and, inversely, (iii) new hires will be specially beneficial if they imply the firms' access to more skilled workers. These relations are expected to hold even when other variables which were systematically found to be relevant for firm survival are taken into account.

3. DATA AND DESCRIPTIVE STATISTICS

The data used in this paper was collected by the Portuguese Ministry of Employment and Social Solidarity (MTSS), on the basis of an annual survey that started in 1982 (the data available for this research covers the period 1985-2002). This survey is compulsory for all firms employing paid labour in Portugal, and 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 allow following them over time. In practice, however, while firms are clearly identifiable over the years on the basis of such number, some problems arise in what concerns the longitudinal analysis of workers. To start with, data on workers were not collected in 1990 and 2001, restricting the availability of continuous series to the periods 1985-1989 and 1991-2000. Second, the quality control of data related to employees has been increasing over the years; while it is possible to have reliable data on individual trajectories in more recent periods, it seems reasonable to renounce to the use of the data corresponding to years before 1990.
Thus, the database used in the present analysis includes all firms in the MTSS's files that comply with two criteria: (i) they were founded between 1991 and 2000 (including the limiting years)[3], and (ii) they are considered as KIBS firms on the basis of their industry classification code (see technical annex). These criteria lead to the inclusion of 9.996 firms in the dataset and, after the necessary data quality checks, of 50.283 individuals employed by those firms.[4]

Drawing on the information available in the MTSS's files, the following variables were computed for each firm at each period: total employment, proportion of graduates among the workforce (as a proxy of human capital), churning rates[5], proportion of hires by level of education (e.g., the number of people with basic education accessing the firm divided by the total employment), proportion of

[3] Restricting the scope of the analysis to new firms allows to keep track of each firm in the database since its foundation until its death or, alternatively, until the year 2002, thus avoiding the problem of left-censoring in the estimation of the empirical model of survival – see section 4 below.
[4] Further issues and problems that arise in preparing the longitudinal series, and the way they were dealt with in the present context, are discussed in more detail in the technical annex.
[5] Following Lane et al. (1996), churning flows are computed at each period as the difference between total worker turnover (i.e., the sum of hires and separations occurring in that period) and the absolute value of net job changes. I.e., CF=WF-|H-S|, where CF are the churning flows, WF are the total worker flows, H are the hires, and S stand for the separations in the period. To obtain the corresponding rates, the churning flows of each firm were simply divided by its total employment.

separations by level of education (e.g., the number of people with higher education leaving the firm divided by the total employment).

The tables presented below give information about the main features of the data which will be used in the analysis. Table 1 shows the dynamics of entry and exit of the firms included in the database. It is possible to see in this table that the number of firms entering and exiting the market tends to increase over the decade, reflecting the growth in the KIBS industries during that period. Furthermore, both entry and exit denote to some extent the evolution of the business cycle: particularly noteworthy is the fact that the data for 1993 (the only year during the 1990s in which Portugal experienced a negative growth in the GDP) reveal a significant decrease in entries and a substantial increase in the number of exiting firms.

The data shown in table 1 also shows that a significant proportion of firms in each cohort exits the market during their first few years: in fact, the percentage of firms that exit after the first year is always higher than 15%, and the number of exits after two years is in no case smaller that 25%. This confirms the idea that the probability of survival is particularly low for younger firms. Finally, the data in table 1 allows one to infer the importance of right-censoring in the 1991-2000 sample (which will be used in the regression)[6]: the average proportion of censored cases is 58,4%, varying between 27,2% for the 1991 cohort and 77,9% for the 2000 cohort.

Table 1 – Firm entry, and firm exit
(number of firms by entry cohort)

		Year of exit[#]												Total entry
		1991	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	
Year of entry	**1991**	176	81	74	40	20	17	8	7	8	18	9	159	617
	1992		166	129	65	42	18	12	9	9	14	13	189	666
	1993			201	62	31	23	12	15	9	11	15	187	566
	1994				213	71	57	49	29	34	25	30	321	829
	1995					151	90	53	43	40	34	44	318	773
	1996						136	78	61	49	62	51	417	854
	1997							169	88	64	65	81	494	961
	1998								193	111	91	106	674	1.175
	1999									196	111	163	724	1.194
	2000										521	359	1.481	2.361
Exits		176	247	404	380	315	341	381	445	520	952	871	-	-

[#] For 2002 it is not possible to distinguish between real exists and right-censoring.

[6] Since the period under analysis ends in 2000, the information relative to 2001 and 2002 can be used to check whether the firms that were registered in 2000 survived after that year (i.e., are right censored) or they exited the market in that year.

Table 2 gives information about the average sizes of firms with different ages. In this respect, the growth patterns of the firms in this database are not different from what has been found in other contexts – that is, firms typically enter the market at the lower size classes, and then they either grow and survive, or they exit the market. As a result, the size of firms typically increases monotonically with firms' age.

Table 2 – Relation between firm size and firm age
(average sizes by entry cohort)

	Number of years since entry									
Year of entry	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1991	3,8	5,9	6,3	12,6	17,6	18,9	22,7	34,3	22,0	34,3
1992	3,5	4,3	4,7	4,9	6,3	7,6	8,2	9,1	10,1	
1993	3,4	4,7	5,3	5,7	7,1	8,0	8,0	8,3		
1994	3,2	4,9	6,4	7,9	11,2	14,1	14,4			
1995	2,8	4,1	5,9	8,2	10,7	13,4				
1996	3,1	4,6	5,5	5,8	8,0					
1997	3,1	4,0	4,7	5,1						
1998	3,3	4,8	6,3							
1999	3,4	4,6								
2000	3,1									
Total	**3,2**	**4,6**	**5,7**	**6,9**	**10,0**	**12,6**	**13,3**	**16,8**	**15,7**	**34,3**

Finally, table 3 displays information on the other side of the labour market of KIBS industries – more specifically, on the demographic characteristics of the individuals in the database. We can see in the table that the growth of KIBS industries during the 1990s has benefited from the inflow of new workers to the labour market; even in the last year of the period under analysis, workers in these industries who had never been registered in the MTSS's files represented ¼ of KIBS's employees. It is also clear from the table that the rate of worker turnover is significant: the annual proportion of workers who have stayed in the same firm since the previous year is always smaller than one half. Finally, table 3 contains information about the level of education attainment of KIBS's workers; for example, in the year 2000, 18% of these individuals held an university degree, 36% had completed between 10 and 12 years of schooling, 29% achieved no more than the compulsory level of schooling (it was 6 years until the early 1990s and 9 years after that), and 9% had at most the very basic level of formal education (4 years). When these figures are compared with the ones concerning all the workers that are registered in the MTSS database, it becomes clear the knowledge-intensive character of the KIBS industries in the Portuguese context: in 2000, the proportions for the complete set of workers, from the highest to the lowest level of education, were 6,2%, 17,4%, 40,4% and 36,1%.

Table 3 – Demographic characteristics of the individuals in the database

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
% of stayers	-	34%	36%	26%	37%	34%	33%	32%	31%	33%
% of movers	-	24%	33%	38%	31%	36%	35%	36%	44%	42%
% of labour market entrants	-	42%	31%	36%	32%	30%	31%	31%	25%	25%
% holding university degree	13%	12%	13%	14%	14%	16%	17%	19%	20%	18%
% 10 to 12 years of shooling	32%	29%	29%	31%	32%	34%	34%	34%	37%	36%
% 6 to 9 years of shooling	36%	34%	33%	33%	31%	33%	32%	32%	29%	29%
% < 4 years of schooling	21%	18%	18%	15%	14%	14%	14%	11%	11%	9%
Total number of individuals	4410	6658	8137	10402	13201	15435	18959	23496	26117	30528

4. METHOD

The relation between labour mobility and firm survival is here 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). Statistical models of duration data (or survival time data) are particularly adequate to analyse situations in which individuals can change between states with the passage of time. In the present case, a survival model is used in order to understand the factors determining the survival prospects of firms.

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 it stayed in the market until *t*. Formally,

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

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 been often used in this context is the Proportional Hazards (PH) model. Such framework is characterised by its satisfying a separability assumption:

(2) $h(t; X) = h_0(t)\, e^{X'\beta}$

where $h_0(t)$ is a 'baseline hazard' function which depends on *t*, and $e^{X'\beta}$ is a person 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 assumption of the 'baseline hazard' being monotonically dependent on *t* is frequently presented as a crucial shortcoming of the PH approach. In fact, the idea of a monotonic duration dependence is often not consistent with what is observed in the data: for example, the survival chances of firms may actually decrease in the early phases of their life (as initial resources are being exhausted and returns are only starting to take-off) and start to increase afterwards (since the surviving firms are the ones who were able to achieved high performance levels and assure regular returns).

One way to overcome this problem is to use a parametric approach, in which the shape of the hazard function is assumed to follow a certain distribution (the parameters of which have themselves to be estimated empirically), which can assume a number of different patterns. The model used in this paper constitutes an alternative to such parametric models, since the problem of the monotonic duration dependence inherent to the PH model is here solved without having to completely characterise the shape of the hazard function (as is the case with the parametric approach).

The basic idea underlying the piecewise-constant hazard model 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, but it may differ between intervals. Then, the hazard function becomes:

$$(3) \qquad h(t;X) = \begin{cases} h_1\, e^{X_1'\beta} & 0 < \mathrm{t} \le \mathrm{c}_1 \\ h_2\, e^{X_2'\beta} & \mathrm{c}_1 < \mathrm{t} \le \mathrm{c}_2 \\ \ldots & \\ h_K\, e^{X_K'\beta} & \mathrm{c}_{\mathrm{K-1}} < \mathrm{t} \end{cases}$$

where the time axis is divided into K intervals by points c_1, c_2 …, 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 to incorporate time-varying covariates – a relevant feature in the context of the present paper, where the aim is to study the impact of changing patterns of labour mobility on the survival prospects of firms

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 $c_K=\infty$).[7] Thus, the individual contribution to the Likelihood will be:

$$(4) \qquad L_i = \left[f(c_k)^{\delta_i} . S(c_{k-1})^{1-\delta_i} \right]^{d_{ik}} ,$$

with

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

and

$$\begin{cases} \delta_{\text{i}} = 1 & \text{if} \quad \text{firm i exits in the interval} \left] \text{c}_{\text{k-1}}, \text{c}_{\text{k}} \right] \\ \delta_{\text{i}} = 0 & \text{if} \quad \text{firm i is censored in the interval} \left] \text{c}_{\text{k-1}}, \text{c}_{\text{k}} \right] \end{cases} ,$$

Noting that $f(c_i)$, the probability that firm i exits 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 becomes

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

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

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

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

[7] 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 applications.

Suppose now that there are firm-specific unknown factors that may play a part in determining its survival rate in the market. If some unobserved characteristic intensifies the transition into exiting the market, then the sample will increasingly be made of firms that do not possess that characteristic. The latter firms may thus come to dominate the sample thereby introducing a systematic bias towards negative duration dependence. This is a well known fact in the literature (see, for instance, Heckman and Singer, 1984 or Lancaster, 1990).

For the sake of simplicity, a conventional parametric form, namely a Gamma distribution with unit mean and variance σ^2 is selected to account for the unmeasured heterogeneity. It will allow the use of a closed form for the survival function, which now becomes

$$S(c_{k_i-1}) = \left(1+\sigma^2\left\{\sum_{l=1}^{k-1} h_l\, e^{X_l'\beta}\left(c_l - c_{l-1}\right)\right\}\right)^{-\frac{1}{\sigma^2}}, \qquad \mathrm{k} = 2,\ldots,\mathrm{K}$$

The remaining formulae remain unchanged.

5. RESULTS AND DISCUSSION

At the end of section 2 it was suggested that the following relations between labour mobility and the hazards of firms were expected to hold in the context of industries such as KIBS: (i) churning rates will be negatively related with firms' survival chances; (ii) job match dissolutions which involved individuals with more human capital will increase the hazard rate of firms; and, inversely, (iii) hiring better workers will decrease the hazard rates of firms. These relations should hold even when other variables which were systematically found to be relevant for firm survival are taken into account.

We start by discussing the role of churning rates in determining the hazard rates, on the basis of the results presented in table 4.

In regression (1) only the current churning rate was included among the regressors (the other 10 coefficients correspond to the 'baseline hazards' of each interval). The coefficients are all significant and their values are as expected: the hazard rate is positively related with churning, and is typically decreasing with firms' age (the hazard-age relation is not entirely monotonic – the probability of hazard decreases from the first to the eight year, but increases slightly in the subsequent years).
These results do not change dramatically when one controls for other variables which have often found to be relevant in determining firms' survival chances. Regressions (2) and (3) have considered the role

of firm size. In the former case, the current size was included in the regression without changing the previous results; the value of its coefficient is also significant and has the expected sign (i.e., bigger firms have higher survival chances), but its impact is small. It has been argued before that current size is often not a sufficient statistic for predicting survival (contrarily to what is suggested by some models of firms' growth, as the one by Jovanovic, 1982), and it is therefore advisable to consider the effects of both the size of firms at entry and their rate of growth afterwards (see, e.g., Mata et al., 1995). Thus, these two variables replace current size in regression (3); the previous results do not change considerably, and the value of the coefficients of the new regressors are as expected – they are both negative and their absolute value is nearly four times higher than the one found in regression (2) (confirming the idea that both initial and current size matter for predicting survival).

Table 4 – Churning as a determinant of hazard rates

	(1)	(2)	(3)	(4)	(5)
Firm age = 10	-2.341**	-2.264**	-2.186**	-1.726**	-1.818**
Firm age = 9	-2.238**	-2.164**	-2.077**	-1.563**	-1.659**
Firm age = 8	-2.798**	-2.734**	-2.652**	-2.089**	-2.089**
Firm age = 7	-2.618**	-2.563**	-2.478**	-1.921**	-1.920**
Firm age = 6	-2.328**	-2.273**	-2.192**	-1.658**	-1.692**
Firm age = 5	-2.228**	-2.178**	-2.102**	-1.595**	-1.678**
Firm age = 4	-2.064**	-2.024**	-1.950**	-1.481**	-1.534**
Firm age = 3	-1.949**	-1.915**	-1.844**	-1.443**	-1.465**
Firm age = 2	-1.810**	-1.781**	-1.714**	-1.312**	-1.308**
Firm age = 1	-1.199**	-1.176**	-1.113**	-.7042**	-.702**
Current size		-.0071**			
Initial size			-.028**	-.0304**	-.031**
Growth since birth			-.027**	-.0255**	-.027**
GDP growth				-.1343**	-.133**
Churning at t	.448**	.462**	.477**	.464**	.451**
Churning at t-1					.241**
Churning at t-2					.278**
Churning at t-3					.286 *
Churning at t-4					-.487
Churning at t-5					-.132
Churning at t-6					-.067
Churning at t-7					.630
Churning at t-8					-.200
Log likelihood	-10637.3	-10626.3	-10605.4	-10529.4	-10519.9

** significant at a 5% level

* significant at a 10% level

Regression (4) adds annual GDP growth to the vector of independent variables. The results of this regression confirm the suspicion that was raised when discussing the contents of table 1, concerning the influence of the business cycle in the dynamics of KIBS industries. The sign of the GDP coefficient shows that the hazards of firms decrease with the improvement in the macroeconomic environment. Furthermore, the inclusion of this variable partially changes the results obtained in the previous regressions: the 'baseline hazards' of the higher intervals are no longer significant, suggesting the effect of age on survival is only relevant for those firms in the first years of their lives. On the contrary, the impact of current churning is a strong and significant predictor of firms' hazards in all the regressions from (1) to (4).

The interpretation of this robust impact of churning on survival is not straightforward. As was explained before, churning consists in those hires and separations of workers that exceed what would be necessary to accommodate the changes in firms' sizes (see footnote 4). Then, one possible way to interpret the results related to the churning coefficient in regressions (1) to (4) is to suggest (in line with the discussion in section 2) that high churning firms are more prone to organisational disruption and, therefore, have lower survival chances. However, the causality could be reversed by noticing that many workers anticipate the downfall of their employing firms, and quit before the dissolution of those firms. Regression (5) tries to analyse these issues by including several lags of the churning variable. The results show that hazard rates are significantly (and positively) related to churning up to the second lag (up to the third, at a 10% level of significance). While this does not demonstrate that churning actually causes the dissolution of firms (both aspects can be determined by a third cause, such as incompetence at the managerial level), it does reinforce the notion that high churning precedes (and probably affects) the exit of firms.

Although the results presented up to this point add to the scarce evidence on the relation between worker turnover and firm survival, they essentially confirm the patterns that were identified in other studies (see Lane et al., 1996; and Burgess et al., 2000). Notwithstanding their importance (which is considerable, given the scarcity of studies on this type of subject), the results concerning the impact of churning on firm survival are not very informative about the relevance of the characteristics of those individuals involved in the labour flows. In fact, one should not expect that workers' hires and separations have similar impacts on firms regardless of the individuals who are actual accessing or leaving the firm. More specifically, the impact of hires and separations is probably higher when more human capital is involved.

The MTSS's database allows an approximation to this problem by providing information about educational background of individual workers. Regression (6) incorporates this kind of information by including as independent variables the proportion of workers accessing and leaving each firm at each level of education (as a percentage of total employment), as well as the current proportion of graduates (see table 5).

Table 5 – Educational level of hires and separations as determinants of hazard rates

	(6)	
Firm age = 10	-1.814	**
Firm age = 9	-1.733	**
Firm age = 8	-2.182	**
Firm age = 7	-2.020	**
Firm age = 6	-1.736	**
Firm age = 5	-1.702	**
Firm age = 4	-1.574	**
Firm age = 3	-1.494	**
Firm age = 2	-1.338	**
Firm age = 1	-.741	**
Current Size	-.006	**
Proportion of graduates	-.246	**
GDP growth	-.128	**
Churning at t	.304	**
% Basic education hires	.413	
% Compulsory education hires	-.307	
% Secondary education hires	-.288	**
% Graduate hires	-.542	**
% Basic education separations	-.140	
% Compulsory education separations	.247	**
% Secondary education separations	.489	**
% Graduate separations	.565	**
Log likelihood	-10474.2	

** significant at a 5% level

* significant at a 10% level

The results displayed in table 5 confirm the relevance of the characteristics of turnover individuals in relation to firm survival. The values of the coefficients presented in the table show that the impact on the hazard rates increases (in absolute terms) from the lower to the higher levels of education, both for hires and separations. Furthermore, the coefficients are particular significant at the highest educations levels, suggesting that the relation between educational background of individual 'movers' and firms' survival is especially robust in those cases.

Again, one can revert the direction of causality, and suggest that: (i) firms' with good survival prospects can more easily attract highly skilled workers than dying firms; and (ii) skilled workers are the first to leave firms with low survival chances (because they can more easily find alternative jobs). Once more, in order to investigate deeper those alternative explanations, We have estimated another regression which includes two-year lags of hires and separations for different educational levels, controlling for the effect of the initial proportion of graduates. The results are presented in table 6.

Table 6 – Educational level of hires and separations as determinants of hazard rates

	(7)		(8)	
Firm age = 10	-1.843	**	1.853	**
Firm age = 9	-1.774	**	1.801	**
Firm age = 8	-2.212	**	1.054	**
Firm age = 7	-2.039	**	1.094	**
Firm age = 6	-1.771	**	1.018	**
Firm age = 5	-1.719	**	.747	**
Firm age = 4	-1.553	**	.593	**
Firm age = 3	-1.483	**	.233	
Firm age = 2	-1.353	**	-.052	
Firm age = 1	-.748	**	.032	
Current size	-.006	**	-.003	*
Initial proportion of graduates	-.212	**	-.419	**
GDP growth	-.127	**	-.242	**
Churning at t	.299	**	.255	**
Churning at t-1	.275	**	.333	**
Churning at t-2	.146		.290	
Graduate hires at t (as % of size)	-.639	**	-.781	**
Graduate hires at t-1 (as % of size)	-.704	**	-1.168	**
Graduate hires at t-2 (as % of size)	-1.615	**	-2.334	**
Graduate separations at t (as % of size)	.664	**	1.196	**
Graduate separations at t-1 (as % of size)	.832	**	1.325	**
Graduate separations at t-2 (as % of size)	.974	**	1.506	**
Secondary school hires at t (as % of size)	-.267	**	-.260	*
Secondary school hires at t-1 (as % of size)	-.793	**	-.937	**
Secondary school hires at t-2 (as % of size)	-.418	*	-.620	**
Secondary school separations at t (as % of size)	.597	**	.959	**
Secondary school separations at t-1 (as % of size)	.355	**	.662	**
Secondary school separations at t-2 (as % of size)	.362	**	.766	**
Sigma	-		1.550	**
Log likelihood	-10447.1		-10399.1	

** significant at a 5% level

* significant at a 10% level

The results of regression (7) clearly suggest that the hire and separation of highly educated employees precedes the closure of firms in at least two years. It is particularly interesting to observe that, in the case of hires and separations of individuals holding a university degree, the strength of the impact increases for more distant years, which further reinforces the idea that the mobility of highly qualified workers affects the survival chances of firms in these industries. This is true even after controlling for the initial proportion of graduates among the firms' employees (which is itself significantly related with firms' survival prospects). That is, increasing or decreasing the percentage of highly educated employees in the workforce has a significant and durable impact on the employing firm's performance, regardless of its initial workforce composition.

It was argued in section 4 that ignoring potential unobserved heterogeneity could lead to biased estimates. Whether or not there is unobserved heterogeneity in model (7) is not the main issue. In fact, the new model controls for it in a parametric way, imposing some more structure on the data. Nevertheless, it is important to check how sensitive are the estimates of model (7) and how previous conclusions stand up to the new specification.

To this end, regression (8) simply introduces a multiplicative term in the hazard, implying the estimation of only one additional parameter. Although some of the variables seem to have lost statistical significance, in fact, estimates remain largely unaffected in the sense that all maintain the same sign and basically preserve the order of magnitude among them. The only exceptions are the baseline hazard parameters. This should not come as a surprise, as it is a consequence of the bias towards *negative duration dependence* – the baseline hazard becomes less decreasing or even increasing when one controls for unobserved heterogeneity (see, for instance, Heckman and Singer, 1984 or Lancaster, 1990). In the end, the previous conclusions seem to hold regardless of the specification adopted.

RESET specification tests[8] were performed for models (7) and (8). The null is accepted in the latter model (p-value equals .818) but is rejected in the former, suggesting model (8) presents a more consistent specification, thus becoming our preferred specification.

[8] In this test, the square of the fitted values are added to the set of regressors of the model. One has to verify if the corresponding parameter estimate is statistically significant. If the null hypothesis is rejected, then the model is not well specified, as a combination of regressors is statistically significative.

6. CONCLUSIONS

The idea that the mobility of workers in the labour market and the dynamics of firms and industries are not entirely independent phenomena is not surprising. Many studies have measured the impact of firms' entry exit, expansion and contraction on the creation and destruction of jobs (for a survey, see Davis and Haltiwanger, 1999). Others have pointed out that industry turbulence affects the labour markets not only in a direct way, but also indirectly through the vacancy chains that are opened and closed by firms' growth/founding and contraction/failure (e.g., by Haveman, 1995). Until now, however, very few studies have focused their attention on the reverse type of effect – that is, the role of labour mobility in determining the dynamics of firms and industries.

This paper intended to contribute to fill that gap in the literature, by studying the labour mobility determinants of firm survival in the context of knowledge-intensive business services industries. These industries typically rely on a highly specialised labour force, and the competition among firms is strongly based on their ability to recruit highly skilled workers and to avoid poaching by competitors – and, in this sense, they are obvious candidates for the type of causal relationship under investigation.

The results of the regressions confirm the initial suspicions. Even after controlling for the usual determinants of firm survival (namely, initial and current size of firms, firms' age, initial and current human capital, and general economic conditions), the impact of several labour mobility variables on the hazards of firms is statistically significant and has the expected direction. The negative relation between firm survival and current and past churning rates (which had been identified in a couple of previous studies) was confirmed. Furthermore, it was shown that the characteristics of the individuals involved in worker turnover is not irrelevant to the firm: the survival prospects of firms systematically increase when they hire educated individuals, and systematically decreases when educated employees separate from the firms ranks. These results hold even when labour mobility variables are introduced in the regression with time lags, which reinforces the notion that worker turnover may actually affect the survival chances of firms (specially when highly educated individuals are involved) – and does not simply reflect an anticipation of firms' dissolution by their employees.

7. REFERENCES

Akerloff, G. and J. Yellen (1986), *Efficiency Wage Models of the Labor Market.* Cambridge University Press: New York.

Audretsch, D. and T. Mahmood (1995), 'New Firm Survival: New Results Using a Hazard Function', *Review of Economics and Statistics* 77(1), 97-103.

Baron, J. (2004), 'Employing Identities in Organisational Ecology', *Industrial and Corporate Change* 13(1), 3-32.

Burgess, S., J. Lane, and D. Stevens (2000), 'Job Flows, Worker Flows, and Churning', *Journal of Labor Economics* 18(3), 473-502.

Davis, S. and J. Haltiwanger (1999), 'Gross Job Flows', in O. Ashenfelter and D. Card (eds), *Handbook of Labor Economics Vol.3,* 2711-805. Elsevier: Amsterdam.

Dunne, T., M. Roberts, and L. Samuelson (1989), 'The Growth and Failure of US Manufacturing Plants', *Quarterly Journal of Economics* 104(4), 671-98.

EMCC (2005), 'Knowledge-intensive business services - what future?', *Sector Futures series on the KIBS sector,* European Foundation for the Improvement of Living and Working Conditions, Ireland.

Haveman, H. (1995), 'The Demographic Methabolism of Organisations: Industry Dynamics, Turnover, and Tenure Distributions', *Administrative Science Quarterly* 40(4), 586-618.

Heckman, J. and B. Singer (1984), 'Econometric Duration Analysis', *Journal of Econometrics*, Annals 1984-1, 63-132.

Jenkins, S. (2004), '*Survival Analysis',* Unpublished manuscript, Institute for Social and Economic Research, University of Essex, Colchester, UK.

Jovanovic, B. (1982), 'Selection and the Evolution of Industry', *Econometrica* 50(3), 649-70.

Lancaster, T. (1990), *Econometric Analysis of Transition Data*. Cambridge University Press: Cambridge, Massachusetts.

Lane, J., A. Isaac, and D. Stevens (1996), ‘Firm Heterogeneity and Worker Turnover’, *Review of Industrial Economics* 11, 275–291.

Mamede, R. (2002), ‘Does Innovation (Really), Matter for Success? The Case of IT Consultancy’, Dinâmia Working Paper No.25/2002.

Mamede, R. (2009), ‘Toward an integrated approach to industry dynamics and labor mobility’, *Industrial and Corporate Change* 18(1), 139-163.

Mata, J. and P. Portugal (1994), ‘Life Duration of New Firms’, *Journal of Industrial Economics* 42(3), 227-245.

Mata, J., P. Portugal and P. Guimarães (1995), ‘The survival of new plants: start-up conditions and post-entry evolution’, *International Journal of Industrial Organisation* 13, 459-481.

Møen, J. (2005), ‘Is Mobility of Technical Personnel a Source of RandD Spillovers?’, *Journal of Labor Economics* 23 (1), 81-114.

Rubalcaba-Bermejo, L. (1999), *Business services in European industry: growth, employment, and competitiveness,* Office for Official Publications of the European Communities: Luxembourg.

Staw, B. (1980), ‘The Consequences of Turnover’, *Journal of Occupational Behaviour* 1(4), 253-73.

Wagner, J. (1999), ‘The Life History of Cohorts of Exits from German Manufacturing’, *Small Business Economics* 13, 71-79.

8. TECHNICAL ANNEX

The database used in this paper includes all firms in the MTSS files that comply with two criteria: (i) they were founded between 1991 and 2000 (including the limiting years), and (ii) they are considered as KIBS firms on the basis of their industry classification code.

The most obvious way to control for the first criterion it to identify the first year a firm was included in the files. It happens, however, that this not guarantee that the firm is actually a new one, due to three possible situations: (i) the firm already existed but was not officially registered, (ii) it was registered with a different name and/or social security number, or (iii) the information about the firm was incorrectly introduced. The MTSS database allows to overcome this problem by taking advantage of different variables. First, firms are given a sequential number as identification code, which means that if *t* is the first year the firm appears in the files, its code number cannot be lower than the highest number among the firms that firstly appeared in the files in year *t-1*. Second, information about individuals includes a question on tenure – and individuals working for new firms cannot have a tenure higher than one year (or two, if one allows for late official registry).

A related question concerns the identification of the time of exit. Since the period under analysis was 1991-2000, and the MTSS files include information on firms until 2002, firms were considered as ceasing to exist in the year after they have been reported for the last time. Again, this does not assure that exit dates are correctly identified: a firm that was reported for the last time in 2000 may reappear in the 2003 files. In fact it is possible to find a few cases of firms that were temporarily absent from the files. However, cases in which firms are absent from the files for two years in a raw are quite exceptional in the complete database, so checking for the presence of the firm in 2001 and 2002 will assure a correct classification of exit dates in virtually every case of KIBS firms.

Concerning the second selection criterion, the use of the industry classification code to identify KIBS firms is not totally straightforward, since the Portuguese classification of economic activities (CAE) has changed between 1994 (CAE rev.1) and 1995 (CAE rev.2).[9] Thus, the set of industries to include in the database had to be defined for each of the two classification systems. From 1991 to 1994, the following industries were classified as KIBS (the number in parenthesis corresponds to the CAE rev.1 code): legal services (8321); accounting and auditing (8322); data processing (8323); engineering,

[9] These are equivalent to the International Standard of Industrial Classifications (ISIC) rev.2 and rev.3, respectively.

architecture and other technical services (8324); advertising (8325); other business services (8329); general research (9114); and scientific and research institutes (932). From 1995 to 2000, the following industries were classified as KIBS (the number in parenthesis corresponds to the CAE rev.2 code): computer and related activities (72); research and development (73); legal services (7411); accounting, book-keeping and auditing (7412); market research and public opinion polling (7413); business and management consulting (7414); engineering, architecture and other technical consultancy (742); technical testing and analysis (743); advertising (744); labour recruitment and provision of personnel (745); investigation and security activities (746); secretariat and translation (7483); other business services (74842); telecommunications (64200); and news agencies (924).[10]

In the original MTSS files there are 21.108 firms which were at least once classified in one of the industries mentioned above, which were reported for the first time after 1990, and which have been reported for the last time until 2000. The following cases have been excluded from the sample used in the present paper: firms that present discontinuities in the series (18,7%), firms that were not always classified as KIBS (12,6%), or firms whose founding date is not consistent with the first inclusion in the files after all the checks mentioned above (32%). This leads to a total number of firms of 9.996 in the dataset used for analysis.

The next step consisted in preparing the longitudinal series of workers. Like in the case of information on firms, in the original MTSS files the data on individual workers were not consolidated over the years. But unlike the case of firms, it is often not possible to clearly identify individuals' trajectories over time. There are two types of reasons for this. First, while the data quality control procedures were quite rigorous in the case of firms, the same did not happen for individuals (the huge number of which – together with the recurrent lack of resources in the Ministry – prevented a thorough quality check); as a result, in many cases some data about individual workers was incorrectly introduced or not introduced at all, which is particularly problematic for the present purposes when it implies the impossibility to unequivocally identify each worker. A second is raised by the fact that it may happen that two different individuals are registered with the same identification code – which may be a consequence of the previous mentioned lack of data quality control, or of the fact that the Portuguese regional centres of Social Security have used for sometime relatively autonomous, and possibly overlapping, sequences of identification codes. In sum, in the original annual files one often finds

[10] These criteria for the selection of KIBS industries does not coincide entirely with the other criteria that have been used in related literature. The need to minimise the mismatches in the definition of KIBS between the two classification systems led me to discard some sub-industries and to include one – news agencies – which is usually left aside.

individual records with duplicate identification codes, or without any individual identification at all. Therefore, if one hopes to build a longitudinal dataset of individual workers, and number of cleansing procedures are required.

The first step was to eliminate those records which do not allow a unequivocal identification of individuals in each annual files. It resulted that this problem was less severe for more recent periods (in which quality checks of data input were significantly improved), than for earlier ones. Together with the total absence of individual data in 1990, this led to the decision to fix 1991 as the starting year of the analysis – in this year, 87% of the individual records included a non-duplicate, valid identification number.

However, one further problem with the data became evident in the process of consolidating the annual files: even if in each year only the records with non-duplicate, valid code numbers are included, this does not guarantee that the records that have the same identification number in different years correspond in fact to the same person (what is to be expected given the problems mentioned above). By comparing the value of variables such as gender or date of birth for different years it is possible to identify does case in which having the same ID code does not mean being the same person. About 13% of individual records were further eliminated as a result of this problem.

The third step consisted in identifying the individuals that were employed by some of the 9.996 firms in the database at some point. This was relatively easy, since the information on individuals is actually provided by their employers, which means that each individual record (in spite of other possible problems) is unequivocally attach to a firm. This led to the identification of 63.989 KIBS workers.

Finally, some of the individual records presented discontinuities in the longitudinal series. While such discontinuities may be related with the problems of data quality there were mentioned above, they may also result from one of the steps mentioned before: in fact, the decision to eliminate all the records with duplicated identification numbers implies that all the workers that have worked for two firms in the same year will be erased from the files (since there will be two records for each of those individuals). Taking this problem into consideration, we have adopted the following solution: when the gaps in individual records affect two subsequent years, these records are erased from the files; in the case of discontinuities affecting only one year, we assume that the corresponding workers have moved between firms in that year (thus, if there is no information about worker i at t but there is information at t and $t-1$, it is assumed that i's employer at t is the same as the one at $t+1$). After this third step it is possible to unequivocally identify a total of 50.283 individuals working for KIBS firms.