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Age and opportunities for promotion*

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Abstract
Using a panel of new firms and their employees, this paper studies the promotion opportunities for older workers within the same firm. Survival analysis suggests that younger employees experience shorter times to promotion than older workers and, therefore, the latter face a smaller likelihood of promotion. Although men are promoted more often than women, empirical results show that women have shorter survival times to promotion than men. Also, previous promotions are stronger determinants of subsequent ones and this finding provides support to the evidence on promotion "fast-tracks".

Keywords: aging, older workers, employment relationships, promotion
JEL classification: J14, J21, D21, J62

1 Introduction

As a response to the challenge of population aging, increasing employment rates of older individuals and delaying their exit from the labor force are the core objectives of active aging policies. As the demographic prevalence of older cohorts grows, so does their relevance in the labor force.

Older workers have been the major contributors to employment growth in the European Union (EU)[1]. Nevertheless, older individuals still face difficulties in what concerns employment[2] and career development opportunities such as promotion. Adams (2002) studies the effect of age discrimination in promotion on wage growth, separations and early retirement, and finds that in firms where older individuals report that younger workers are favored in promotions, older workers face lower wage growth and a greater likelihood of early retirement. Data used are based on reported perceptions by older

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[1] For detailed statistics see European Commission (2008).
[2] As for employment opportunities, empirical studies show that firms employ older workers but, as the former favor long employment relationships, preference goes to hire younger individuals (Daniel and Heywood, 2007; Heywood *et al*, 1999; Hutchens, 1986, 1988).

individuals of their firms' promotion practices. Johnson and Neumark (1997) also suggest that age discrimination is associated with a higher likelihood of job separation together with a smaller propensity to remain employed. Thus, age differences in promotion prospects have practical consequences on the labor force status of older individuals, influencing their retirement decision.

Since age appears to be a disadvantage factor in what labor market opportunities is concerned, this research aims to examine if there are any differences in career development between younger individuals and older ones. This is done employing survival analysis techniques on a sample of new firms and their workers.

We take advantage of a comprehensive data set called *Quadros de Pessoal* (QP). QP is a matched employer-employee longitudinal database that, given the mandatory nature of the underlying survey, covers the population of firms and workers in the private sector. Contrary to other data sets (such as the ones used by McCue (1996), Pergamit and Veum (1999), Francesconi (2001)), the promotion events are not self-reported but are supplied by the firm. This allows for the definition of a benchmark, at least within firms, that reduces measurement errors associated with self-reported data.

Quadros de Pessoal has formerly been used to study the determinants of promotions in the Portuguese labor market. Lima and Pereira (2003) focus on workers' career and wages using a sample of large firms, highlighting the effect of promotions on wage growth, while Lima and Centeno (2003) study the careers of top managers. However, since both these studies centre the attention on particular groups (the former in large firms and the latter in top managers) results cannot be generalized. Lima (2004), Silva and van der Klaauw (2006), and Ferreira (2009) produce a set of results that can be generalized. Yet, none of these studies focuses on the promotion opportunities faced by older individuals.

Do older workers experience the same likelihood of promotion as younger ones? Considering a sample of new firms, our findings suggest that this is not the case: older employees are in fact in disadvantage when it comes to promotion opportunities.

This paper is structured as follows. Section 2 presents a theoretical synopsis on employment relationships and career development. The following section displays previous empirical results on the determinants of promotions. A description of the data set used is presented in Section 4. This section also highlights the survival time characteristic of the data. Section 5 describes and discusses the estimation procedures used and Section 6 reports the empirical results. Finally, Section 7 concludes.

2 Theoretical overview

The study of employment relationships in labor economics has grown in relevance over the last decades. Unequivocal is the statement that long-term employment relationships benefit both employers and workers. These benefits are highlighted, among other authors, by Oi (1962) and Lazear (1979, 1981). As job tenure increases, the employer becomes aware of the quality of the worker, measured by his productivity, and both recognize or not the quality of the match (Jovanovic, 1979). A mismatch leads to job separation while good matches may lead the worker through a defined career path within the firm's hierarchy. The concept of a career is the basic feature of an internal labor market where careers are seen as a sequence of promotions to higher hierarchical levels with higher pay and responsibility (Baker *et al.*, 1994a). Firms implement internal labor markets in which careers and wages are somewhat protected from external labor markets (Baker and Holmstrom, 1995) as a means to motivate workers and, thus, enhance their productivity.

Gibbons (1996) provides an interesting review on the theory of wages and career dynamics within firms. The author mentions four underlying literatures: job assignment, tournaments, human capital and learning.

The job assignment literature (Sattinger, 1975; Rosen, 1982 and Waldman, 1984a) focuses on the assignment of workers to jobs when firms consist of an array of potential job assignments and there exists full information about workers and jobs. The models are static and based on the idea that employees with higher ability should be assigned to jobs where decisions have an impact over a larger scale of operations. However, since the models are static, they cannot explain wage and career dynamics (Gibbons and Waldman, 1999; 2006). Nevertheless, when the firm assigns the worker to a new job it signals information to competing firms about the worker's ability (Waldman, 1984b; Bernhardt and Scoones, 1993). Therefore, the wage increase offered to the employee must be sufficiently high to disincentive competition by other firms.

Lazear[3] and Rosen (1981) and Rosen (1986) see promotions as a prize awarded the winner of a competition. They develop a tournament theory based on a rank-order payment scheme that resembles a contest. Workers are paid a prize that is higher for

[3] Lazear's (1979) theory of deferred compensation can also be seen as a worklife incentive scheme. This theory argues that senior workers receive wages above their marginal product to motivate them during the initial years of their careers (when wages are below their marginal product). Lazear (1999) relates worklife incentive theory to tournament theory but, while tournaments emphasize relative comparisons between workers, worklife incentive schemes are not comparison-based. Also, tournaments highlight wage increases upon promotion, which correspond to job changes whereas worklife incentives focus on pay changes that occur within a job instead of the change between them. But, as Lazear (1999) states, both incentive designs can be at work within the same firm.

workers in upper positions within the firm: the winner is the worker with the highest productivity. This type of incentives is particularly relevant when firms face substantial monitoring costs. Additionally, compensation schemes like rank-order tournaments seem to favor long-run employment relationships between employer and employee. However, there is a drawback associated with this category of incentive schemes: they may induce excess competition among employees and damage worker cooperation. Additionally, tournament theory does not take into consideration the possibility of external competition by other workers, for the same position. Chan (1996) compares the choice between internal promotion and external recruitment within the context of a tournament. He finds that when competition is open to external applicants, internal workers reduce their chance of promotion. But he also suggests that an external applicant is only hired whenever she/he is significantly better that the internal candidate.

Manove (1997) concludes that firms can diminish incentive costs through the definition of a job ladder and offering promotion prospects. That is, it is in the interest of the employer to construct an internal job ladder that induces workers in low paying jobs (hired externally) to offer increased effort as a way of paying for promotion (internal) to high paying jobs.

Investments in human capital may also result in promotions (Becker, 1962). While general training (general human capital accumulation) raises the future marginal product of employees in the firm providing it, it would also increase the workers' marginal product in many other firms. Because of this, the wage of trainees is below their actual marginal product, meaning that employees pay for their general on-the-job training. Conversely, the accumulation of firm-specific human capital, through specific training, increases productivity more in firms providing it. Therefore, and since specific training involves investment by both firm and worker, they have an incentive to engage in a long-term employment relationship. Carmichael (1983) shows that when employers and employees invest in specific human capital, promotions are given to trained workers according to their seniority level.

According to the learning literature, firms do not know about the worker's ability when she/he enters the labor force but, as time goes by, the firm becomes aware of it. Therefore, as tenure in a job increases, the worker's productivity is known more precisely (Jovanovic, 1979) and good performances will be rewarded with higher wages. A promotion may well be the firm's response after learning about the worker's productivity.

Farber and Gibbons (1996) develop a dynamic model of learning and present it as a complement to the human capital model in the explanation of wage dynamics.

Gibbons and Waldman (1999) show that a model that combines features of job assignment, human capital acquisition and learning can capture some of the empirical findings concerning promotion dynamics and wages within firms, such as the positive association between promotions and wage increases or that workers who get large wage increases at one particular job level are more likely to be promoted to the next level.

3 Previous empirical findings

Empirical studies on promotion and career dynamics inside firms do not focus on testing any of the above mentioned theories in particular. Instead, previous research combines features of each of those theories to examine mobility within firms.

Summarizing the empirical results it is possible to verify that promotion rates fall with age and experience. McCue (1996) finds that age and experience are negatively associated with the promotion likelihood, while Pergamit and Veum (1999) present evidence of the statistical non-significance of these variables. However, Adams (2002) shows that in firms where older employees report that younger workers are favored in promotions, the former face lower wage growth and a greater likelihood of early retirement. Thus, promotion practices that favor younger workers are negatively correlated with wage growth of older workers and positively correlated with the retirement decision.

Tenure effects are less consistent, with evidence both for positive and negative effects. McCue (1996), Francesconi (2001) and Lima and Centeno (2003) have found that tenure and promotion probabilities have an inverse U-shaped relationship. Conversely, Abraham and Medoff (1985) suggest that within-firm mobility declines with tenure. Education effects are generally not significant (e.g. Pergamit and Veum, 1999), but when they are, promotion is positively associated with higher levels of education (McCue, 1996).

There is evidence of both higher promotion opportunities for men than for women (Olson and Becker, 1983; Pergamit and Veum, 1999) and of equal gender promotion likelihood (Booth *et al.*, 2003). Lazear and Rosen (1990) conclude that, since the ability standard for promotion is higher for women, more able women will be passed over for promotion by less able men. The fact that women face more non-market opportunities (such as household production) than men works as a penalty, lowering females' promotion probabilities. According to Lazear and Rosen (1990), a higher expected value of home time raises the probability of separation for women which, in turn, increases the levels of ability for promotion by female employees.

Consistent with the "fast-tracks" mentioned by Baker *et al.* (1994a), there is evidence of a positive association between prior promotions and current promotions (Pergamit and Veum, 1999). Workers who have been previously promoted are more likely to be promoted once again.

As for firm characteristics, Pergamit and Veum (1999) and Francesconi (2001) find that larger firms provide better promotion prospects. A similar conclusion is suggested by Topel and Ward (1992) who argue that large firms comprise workers' movements that would otherwise take place between smaller firms. In larger organizations, the existence of an internal labor market allows for career development within the firm, where individuals progress to higher level jobs through promotions (Baker *et al.*, 1994a).

Overall, as a consequence of promotions workers are rewarded with higher wages (Topel and Ward, 1992; Baker *et al.*, 1994b; McCue, 1996; Pergamit and Veum, 1999; Francesconi, 2001).

4 Data

4.1 *Quadros de Pessoal*: a matched employer-employee data set

We use data for the Portuguese economy from eighteen waves of *Quadros de Pessoal*, a matched worker-firm longitudinal data set. Annually, the Portuguese Ministry of Labor and Social Solidarity gathers information on all firms, from the private sector, with wage-earners. Data collection is based on a mandatory response survey to firms.

Quadros de Pessoal includes information on two hundred thousand firms a year, on average, and their workers (over two million a year). Each firm and worker is uniquely identified in the data set and this allows researchers to follow them over time.

Firm level information includes the date of creation, number of establishments, number of workers, sales, industry, and region, among other. Workers' files present data such as age, gender, date of admission into the firm, date of latest promotion, education, hierarchical level, occupation and wages.

The information used in this study covers the 1986-2005 period, with the exceptions of 1990 and 2001 since no worker data is reported for these years. After merging the cross-sectional worker's and firm's files and after some cleaning of the data set (see Appendix

4.A for a detailed description), we obtain a sample with 1,033,767 observations, for 416,170 workers, 44,920 firms and 437,498 matches firm-worker.

The sample includes only new firms. This way, there is no past history of the worker within the firm that we cannot retrieve information about. However, with a sample of new firms, a problem may emerge: new firms experience high death rates. In effect, Mata and Portugal (1994) show that 20% of the firms created in the Portuguese manufacturing industry in 1983 died during the first year and that only half survived for four years. Thus, we keep in the sample firms that survived for at least two years after their creation. Table B1 in Appendix B displays the distribution of these firms' survival times.

4.2 Promotion event data

Allison (1984: 9) defines an event as "some qualitative change that occurs at a specific point in time". In this research, the qualitative change under analysis is a promotion. To study the promotion event and its determinants, a collection of event history (or survival) data is needed. Using longitudinal data like *Quadros de Pessoal* that collects the date of promotion for workers within their firms makes such a study viable. Unlike other studies, the dates of promotion and, therefore, the promotion events are not self-reported. They are provided by the firm, thus less sensitive to measurement errors.

Since we use a sample of newly created firms, the worker's career within the firm is observed until he/she gets a promotion, and thereafter. The promotion event is defined by the variable "date of the latest promotion", which refers to the year and month of the promotion. Due to the format of the variable, time elapsed until promotion is measured in months. Using 20 years of data from *Quadros de Pessoal*, the time to event (or spell length) ranges from 0 to 238 months.[4]

Not only do we know how long it took a worker to get his/her first promotion, but we have also information concerning subsequent spells. This multiple spell data framework means that we can learn about the promotion history of the worker within the same firm. Nevertheless, if promotions measure the success of an employee within a firm, some workers fail to be successful. Effectively, for as long as data are available, some workers were not or have not yet been promoted (the spell end date is unknown), and so the total length of time is unknown. These right-censored observations are also taken into consideration in the treatment of the data. Also, for workers with previous promotion

[4] October is the month of collection for the 2005 survey, the last survey year considered.

events, subsequent spells length may be censored if the follow-up period ends before promotion. Table B2 in Appendix B summarizes the distribution of promotions among workers.

For uncensored observations, the spell lengths until the first promotion were computed as the difference between the date of the first promotion received and the date of admission at the firm. Subsequent spells were defined through the difference between the date of the present promotion and the date of the previously reported promotion.

For right-censored observations, distinction has to be made between those who have never experienced a promotion and those who have previous events. As for the former, the length of the uncompleted spell is given by the date of collection of the survey minus the date of admission at the firm, while for the latter that length is obtained by the difference between the date of collection of the last survey and the date of the last reported promotion.

The final structure of the data considers only one observation per worker and per event[5], since it does not include time varying covariates. Because of this, the sample used in the empirical setting contains 479,308 observations, including 91,214 promotion events (complete spells). The observations refer to 402,463 workers and 44,728 firms. Summary statistics of the all events are shown in Table 1.

Table 1: Descriptive statistics of events

Spells	Frequency	Percent	Survival time		
			25%	50%	75%
Completed	91,214	19.03	12	16	30
Right-censored	388,094	80.97			
Total	479,308	100			

Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.
Note: Survival time is measured in months.

4.3 Promotions and workers' characteristics

Of the 91,214 promotion events considered, more than 70% were awarded to workers aged less than 35 years at hire while only 10% were given to older workers (with 45 or more years of age). The distribution of promotions by age group at hire is presented in Table 2 and it also displays gender differences in the distribution. One fact depicted in Table 2 is that men obtained more than half of the promotions and this distribution towards men increases with the age group at hire (see column (2)). Moreover, it shows that

5 For instance, a worker that did not receive any promotion during the observation period (right-censored observation) contributes with a single "censored" observation to the survival data. For a worker with multiple events, each event represents an observation, and it is assembled as pooled data.

older workers are promoted less often and this evidence is even stronger for older women (column (3)).

Table 2: Distribution of promotion (%) by age group at hire and gender

Age group at hire	All (1)	Men (2)	Women (3)
15-24	38.23	35.94 (49.84)	40.81 (50.16)
25-34	35.24	34.59 (52.03)	35.97 (47.97)
35-44	16.49	17.07 (54.89)	15.83 (45.11)
45-54	7.70	9.13 (62.81)	6.10 (37.19)
55-75	2.34	3.27 (74.10)	1.29 (25.90)
Number of events (percent of total)	91,214 (100)	48,352 (53.01)	42,862 (46.99)

Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.
Notes: 479,308 observations. In parentheses, columns (2) and (3) show the gender distribution of promotions within age group at hire.

The suspicion of fewer chances for promotion for older individuals is reinforced by the data in Table 3 where promotion rates are summarized. Promotion rates decrease with age for both men and women but, with the exception of the 55-75 age group, women have a higher incidence of promotions than men. For instance, almost 21% of the women in the 25-34 age group at hire receive a promotion against 17% of the men. Higher promotion rates for women are also found in the data for Britain used by Booth *et al.* (2003).

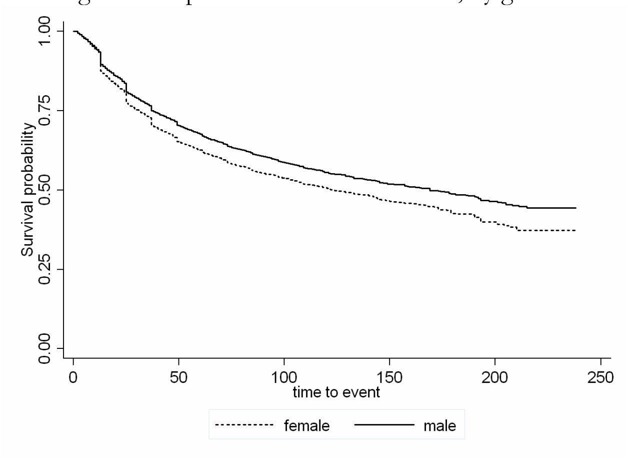
Table 3: Promotion rates by age group at hire and gender

Age group at hire	All (1)	Men (2)	Women (3)
15-24	22.70	21.04	24.62
25-34	18.78	17.29	20.71
35-44	16.44	14.89	18.82
45-54	15.18	14.63	16.23
55-75	12.76	13.26	11.52

Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.
Note: 479,308 observations. Columns (1) to (3) report percentages.

Analysis of the duration data also reveals differences in the survival probability by age group at hire and gender. Figure 1 compares survival probabilities for men and women.

Figure 1: Kaplan-Meier survival curves, by gender

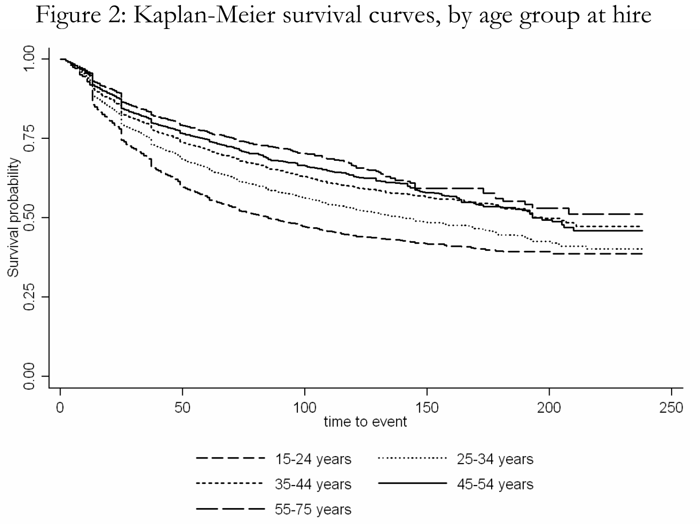


Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.
Note: 479,308 observations. 'Time to event' measures the time to promotion, in months.

Survival curves by gender, presented in Figure 1, show that women face shorter survival times than men, although data from Table 2, column (2), indicates that men get more promotions than women.

Figure 2 plots the Kaplan-Meier survival curves for each age group, showing that younger workers are more likely to receive a promotion than those who are older.

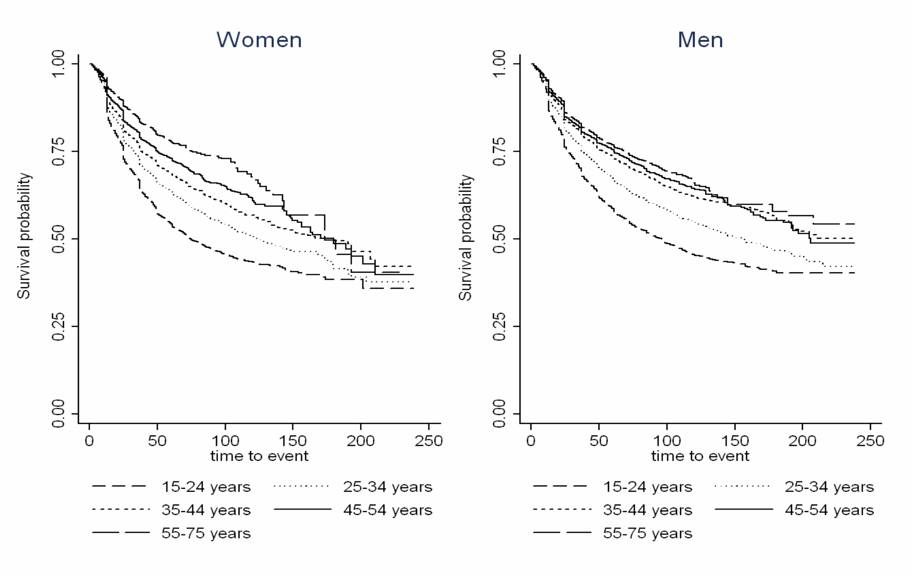
Figure 2: Kaplan-Meier survival curves, by age group at hire



Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.
Note: 479,308 observations. 'Time to event' measures the time to promotion, in months.

Figure 3 also displays the fact that those who are older are less likely to be promoted than those who are younger, regardless of gender.

Figure 3: Kaplan-Meier survival curves, by gender and age group at entry



Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.
Note: 479,308 observations. 'Time to event' measures the time to promotion, in months.

It is plausible to think that firms promote younger workers because older workers have been promoted earlier in their careers and are already at higher levels in the hierarchy. However, in this sample of new firms the hierarchical level of entry into the firm is known and in accordance with the previous statement, older workers should be overrepresented at higher hierarchical levels. Table 4 displays the age distribution of employees by hierarchical level at hire and shows that higher levels (such as top managers or other managers) are predominantly occupied by employees aged 25 to 34.

Table 4: Age distribution (%) by hierarchical level at hire

Age group at hire	Hierarchical level at hire							
	Top managers	Other managers	Foremen/ supervisors	Highly skilled workers	Skilled workers	Semi-skilled workers	Unskilled workers	Apprenctices
15-24	7.65	12.80	10.04	18.20	25.98	32.85	31.69	67.17
25-34	48.82	47.38	36.59	50.40	38.95	34.69	30.04	22.53
35-44	24.33	22.25	29.30	18.57	21.42	19.40	20.30	7.11
45-54	13.60	12.51	17.23	9.36	10.29	9.82	12.25	2.50
55-75	5.60	5.05	6.84	3.47	3.37	3.25	5.73	0.89
Total	100	100	100	100	100	100	100	100

Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.
Note: 479,308 observations.

Additional descriptive statistics of selected variables is presented in Table 5. The sample comprises individuals mainly hired at younger ages where men account for more than half of the observations. Low educational levels is also a feature of the sample since, for almost 60% of the observations, 6 or less years of schooling is the highest attained level of education. Workers enter the firm mainly at lower levels of the hierarchy and, on average, wait 27 months to be promoted.

Table 5: Definition and summary statistics of selected variables

	Definition	Mean (standard deviation)	Percent
Age	Age of the worker, in years	33.244 (10.821)	--
Age group at hire	Age interval, at the time of hiring		
15-24	=1 if the worker aged 15 to 24, inclusive	--	32.06
25-34	=1 if the worker aged 25 to 34, inclusive	--	35.71
35-44	=1 if the worker aged 35 to 44, inclusive	--	19.09
45-54	=1 if the worker aged 45 to 54, inclusive	--	9.66
55-75	=1 if the worker aged 55 to 75, inclusive	--	3.49
Gender	Gender		
Male	=1 if men	--	57.76
Female	=1 if women	--	42.24
Education	Higher attained educational level		
No schooling	=1 if the worker has not attended school	--	.42
2 years	=1 if the worker has two complete years	--	.82
4 years	=1 if the worker completed 4 years	--	29.86
6 years	=1 if the worker completed 6 years	--	27.50
9 years	=1 if the worker completed 9 years	--	18.71
12 years	=1 if the worker graduated from high school	--	16.90
15 years	=1 if the worker completed 15 of education	--	1.35
16 years	=1 if the workers completed 16 or more years	--	4.42
Hierarchical level at entry	Hierarchical level when the workers entered the firm		
Top managers	=1 if top managers	--	3.75
Other managers	=1 if other managers	--	2.52
Foremen/supervisors	=1 if foremen or supervisors	--	2.32
Highly skilled personnel	=1 if highly skilled workers	--	3.99
Skilled personnel	=1 if skilled workers	--	45.06
Semi-skilled personnel	=1 if semi-skilled workers	--	14.03
Unskilled personnel	=1 if unskilled workers	--	13.68
Apprentices	=1 if apprentices	--	14.65
Hierarchical level	Current hierarchical level		
Top managers	=1 if top managers	--	3.83
Other managers	=1 if other managers	--	2.73
Foremen/supervisors	=1 if foremen or supervisors	--	2.99
Highly skilled personnel	=1 if highly skilled workers	--	4.46
Skilled personnel	=1 if skilled workers	--	47.95
Semi-skilled personnel	=1 if semi-skilled workers	--	14.77
Unskilled personnel	=1 if unskilled workers	--	12.54
Apprentices	=1 if apprentices	--	10.73
Previous events	Number of prior promotions	.176 (.586)	--
Tenure (in months)	Tenure at the firm, in months	32.518 (32.834)	--
Time to event (in months)	Survival time to promotion, in months	26.944 (27.829)	--
Firm size (log of number of employees)	Size of the firm, as the logarithm of the number of employees	2.836 (1.531)	--

Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.
Note: 479,308 observations.

5 Parametric models for survival analysis

5.1 Choosing a model

Parametric models for event data may assume two forms: accelerate failure time (AFT) models or proportional hazard (PH) models.[6]

Consider t to be the survival time to an event. An AFT model starts by modelling ln t rather than t. In a log linear form, the regression model can be written as:

$$\ln t = \boldsymbol{x}'\boldsymbol{\beta} + u$$

where $\boldsymbol{x}$ is a vector of covariates, $\boldsymbol{\beta}$ is the vector of regression coefficients, and u represents the error term with a probability density function given by $f(.)$. The distributional form of the error term u determines the AFT model (Cameron and Trivedi, 2005). If the function $f(.)$ has normal density, then the above model is called a lognormal regression model. Alternatively, if $f(.)$ is of logistic density, then a log-logistic regression model is in order. When $f(.)$ is an extreme-value density, an exponential or Weibull regression models are obtained. A generalized gamma model (that assumes a gamma distribution), nesting the Weibull or lognormal models, is also a parametric possibility.[7]

AFT models change the time scale by a factor of $\exp(-\boldsymbol{x\beta})$: if it is greater than 1, time is accelerated and if that factor is less than 1, time is decelerated. This means that if an individual at the baseline faces a probability of survival past time t equal to $S(t)$, the survivor function, then an individual with covariates $\boldsymbol{x}$ would experience probability of survival past time t equal to $S(t)$ evaluated at the point $\exp(-\boldsymbol{x\beta})t$. This implies a deceleration of time with the increase of a covariate. Under AFT, the impact of the regressors is assumed to act additively on the log time scale and, thus, multiplicatively on the time scale itself. The parameters represent the effect of the covariates on the log time scale.

AFT models measure the direct effect of the independent variables on the survival time instead of the hazard as in the PH models. This allows for an easier interpretation of the results because the parameters measure the effect of the correspondent covariate on the mean survival time.

[6] A comparison between proportional hazards and accelerate failure time models is provided by Patel *et al.* (2006).

[7] The generalized gamma distribution has two ancillary parameters: sigma and kappa. The Weibull distribution is a special case of the generalized gamma when kappa equals 1. When kappa equals zero, it reflects the lognormal distribution.

In the PH model, the regressors have a multiplicative impact on the hazard function:

$$h(t) = h_0(t)g(\boldsymbol{x})$$

The function $h_0(t)$ may assume a parametric form, such as Weibull, exponential or Gompertz. $g(\boldsymbol{x})$ is a non-negative function of regressors. The model includes an intercept term β_0, and since letting $g(\boldsymbol{x}) = \exp(\boldsymbol{x}\beta)$ is a common option, $h_0(t) = \exp(\beta_0)$ is the baseline hazard function. Thus, the baseline hazard function is the hazard when all covariates are zero. That is, the intercept term can be used to scale the baseline hazard. Nevertheless, if the function $h_0(t)$ is not specified it yields the Cox proportional hazard model. The hazard of the event of interest in one group is a constant multiple of the hazard in the other group. In these models, the parameters represent the log hazard ratios which, exponentiated, provide the hazard ratios.

Patel *et al.* (2006) underline that although the PH and AFT metrics are often thought of two distinct frameworks, they are connected since the exponential and the Weibull models can be implemented as both AFT and PH models. The authors additionally point out that the Weibull model often gives similar results to the more general PH model as for the effects of the covariates and, so, the AFT model can be considered as a very general approach that contains a specific class of PH models.

Since there is an array of possible distributional forms and corresponding parametric models, how can selection be made? When parametric models are nested, likelihood-ratio or Wald tests may be used to choose between alternatives. This can be done to discriminate between Weibull versus exponential or between gamma versus lognormal or Weibull.

Nonetheless, when nesting is not evidenced, likelihood-ratio or Wald tests are not appropriate and an alternative statistic has to be used. A popular one is the Akaike information criterion (AIC). Considering this, even though the model that best fits the data is the one with the largest log-likelihood, the preferred model is the one with smallest AIC value.

5.2 Models with frailty and shared frailty[8]

The above parametric models are able to explain the variability in observed time to failure. However, both observed and unobserved heterogeneity affect survival times. Due to omitted variables, some unexplained variability or overdispersion may remain and, hence, standard parametric survival models will not take into consideration why individuals

[8] Gutierrez (2002), Cameron and Trivedi (2005) and Stata (2007) provide a good explanation of these models.

with shorter times to failure are more frail than others. That is, controlling for observed heterogeneity, individuals with unobserved characteristics associated with shorter times to failure leave the state more quickly than others; in the presence of unobserved heterogeneity even subjects with the same values of all regressors may experience different hazards. In this case, the estimate of the hazard will be an underestimate of the 'true' one (see Jenkins, 2004). When unobserved heterogeneity (also called 'frailty' in survival literature) is not account for, its effect is confounded with the baseline hazard.

A frailty model is a survival model with unobserved heterogeneity for it attempts to measure that overdispersion. The frailty is included, in each row, as an unobservable multiplicative effect, α, on the hazard function:

$$h(t \mid \alpha) = \alpha h(t)$$

$h(t)$ is a nonfrailty hazard function, α is a random positive effect that, for identification, is assumed to have mean 1 and variance θ.

Conditional on the frailty, the survivor function is now given by

$$S(t \mid \alpha) = \exp\left[-\int_0^t h(u \mid \alpha) du\right] = \exp\left[-\alpha \int_0^t \frac{f(u)}{S(u)} du\right] = [S(t)]^\alpha$$

where $S(t)$ is the survivor function corresponding to the hazard function $h(t)$.

Because α is unobservable, it has to be integrated out of the conditional survivor function $S(t \mid \alpha)$ in order to achieve the unconditional survivor function. Considering that the probability density function of α is given by $g(\alpha)$, a frailty model can be estimated following

$$S_\theta(t) = \int_0^\infty S(t \mid \alpha) g(\alpha) d\alpha = \int_0^\infty [S(t)]^\alpha g(\alpha) d\alpha$$

The unconditional hazard and density functions can be obtained from the unconditional survivor function as $h_\theta(t) = \dfrac{f_\theta(t)}{S_\theta(t)}$ and $f_\theta(t) = -\dfrac{dS_\theta(t)}{dt}$, respectively.

Therefore, compared to a standard parametric model, a frailty survival model additionally estimates the parameter θ, which is an overdispersion parameter.

For mathematical tractability, the choice of the frailty distribution $g(\alpha)$ rests on either the inverse-Gaussian distribution, with parameters 1 and $\dfrac{1}{\theta}$, or the gamma distribution with $\dfrac{1}{\theta}$ and θ as distributional parameters.

In spite of the frailty distribution chosen, $\lim_{\theta \to 0} S_\theta(t) = S(t)$. This means that, when there is no unobservable heterogeneity, the frailty model reduces to $S(t)$.

Using frailty models, distinction has to be made between the hazard faced by the individual, $\alpha h(t)$, and the hazard for the population, $h_\theta(t)$. Correspondingly, an individual has a probability of survival past time t equal to $[S(t)]^\alpha$, whilst $S_\theta(t)$ measures the proportion of the population that survives past time t.[9]

A shared frailty model is a generalization of the frailty models, where the frailty is considered to be group specific. Thus, in shared frailty models, where individuals are allowed to share the same frailty value, the frailty can be used to model intragroup correlation. It is the equivalent to a random effects panel data model (Gutierrez, 2002).

For each observation from the ith group, in a shared frailty model the hazard becomes

$$h(t \mid \alpha_i) = \alpha_i h(t \mid \boldsymbol{x})$$

where α_i represents the frailty shared among group i and $h(t \mid \boldsymbol{x})$ is the individual hazard given regressors $\boldsymbol{x}$.

Therefore, the subjects within a group are correlated since they share a common frailty. In this research we consider three possible "groups": the worker, the firm, and the match worker-firm.

Under an omitted variables scenario, a frailty model could be used when suspecting for the existence of unobserved heterogeneity within the group, while a shared frailty model could be specified in the presence of a latent common group effect.

5.3 Occurrence dependence

Dealing with multiple record/multiple events brings some concerns to the analysis. Specifically, it stresses the problem of event dependence. Hence, one assumption that has to be made is that the dependence of the hazard on time since last promotion has the same distributional form for each successive promotion. A second assumption required is that, for each individual, the multiple events must be independent.

As suggested by Allison (1984), the consequences of violating the occurrence independence assumption can be minimized through the consideration, in the model, of

[9] Using the Stata 11 command – `streg` – to fit parametric survival models, when specifying the option – `distribution( )` – a model for an individual with frailty equal to 1 will be specified; recall that when $\alpha = 1, [S(t)]^\alpha = S(t)$. However, specifying – `frailty(distribution)` – determines which of the two above forms for $S_\theta(t)$ is used.

covariates that capture the workers' previous promotion history. To do so, we include in the specification a variable that accounts for the number of prior promotions: *Previous events*. Also, the length of the previous spell is set to zero when no previous spell is observed.

For comparison, we estimate duration models for the first promotion as well as models for all promotions. This is done in order to examine potential differences between the distributions of time to first promotion and of all events.

6 Estimation results

6.1 First promotion

The effect of selected covariates on the hazard (PH models) and on the survival time to first promotion (AFT models) is, respectively, exhibited in Tables 6 and 7.[10] In the PH form, each regression coefficient indicates the proportional effect on the hazard of absolute changes in the respective covariate. Thus, a negative coefficient reflects a smaller hazard while a positive coefficient represents a higher hazard of promotion. Table 6 presents the results for three different specifications: exponential, Weibull, and Gompertz.

From Table 6, we conclude for the inappropriateness of the exponential model after performing a test (t-statistic=69.64, p-value=0) on the hypothesis that the ancillary parameter (the shape parameter) in the Weibull model is equal to 1. Additionally, the Weibull model performs better than Gompertz since the former shows both a higher log-likelihood and a smaller AIC value.

AFT metrics comparison is made in Table 7. In these models, positive coefficients reveal higher survival times or, which is the same, longer time elapsed until a promotion. On the other hand, negative coefficients mean shorter survival times. Additionally, an AFT regression coefficient relates proportionate changes in survival time to a unit change in a given covariate, *ceteris paribus*, since $\beta_k = \dfrac{\partial \ln(t)}{\partial x_k}$.

[10] We have also estimated a semi-parametric Cox proportional hazards model. No significant differences in the coefficients were encountered.

Table 6: Proportional hazard models' coefficients: first promotion

Variables	Exponential (1)	Weibull (2)	Gompertz (3)
Age group at hire			
[15,25)	.0538	.0621	.0560
	(.0100)	(.0100)	(.0100)
[35,45)	-.0615	-.0729	-.0653
	(.0120)	(.0120)	(.0120)
[45,55)	-.1112	-.1281	-.1163
	(.0161)	(.0161)	(.0161)
[55,75]	-.2326	-.2565	-.2399
	(.0258)	(.0256)	(.0258)
Male	-.0538	-.0528	-.0542
	(.0087)	(.0087)	(.0087)
Education			
No schooling	-.2542	-.2695	-.2580
	(.0758)	(.0758)	(.0758)
2 years	-.1555	-.1340	-.1492
	(.0521)	(.0521)	(.0521)
6 years	.1624	.1863	.1707
	(.0111)	(.0111)	(.0111)
9 years	.3076	.3629	.3244
	(.0131)	(.0131)	(.0131)
12 years	.4279	.4756	.4434
	(.0139)	(.0139)	(.0139)
15 years	.4782	.5526	.5022
	(.0357)	(.0357)	(.0357)
16 years	.5038	.5952	.5331
	(.0262)	(.0262)	(.0262)
Hierarchical level at hire			
Top managers	-.2978	-.3457	-.3118
	(.0263)	(.0263)	(.0263)
Other managers	-.2101	-.2537	-.2224
	(.0287)	(.0287)	(.0287)
Foremen/ supervisors	-.1291	-.1700	-.1416
	(.0272)	(.0273)	(.0273)
Highly skilled	.1591	.1489	.1562
	(.0202)	(.0202)	(.0202)
Semi-skilled	.1244	.1407	.1282
	(.0125)	(.0125)	(.0125)
Unskilled	.1705	.2088	.1803
	(.0138)	(.0138)	(.0138)
Apprentices	.4562	.4852	.4635
	(.0116)	(.0116)	(.0116)
Firm size	.2319	.2468	.2352
	(.0029)	(.0029)	(.0029)
Constant	-7.2673	-8.2459	-7.3831
	(.0200)	(.0255)	(.0213)
Ancillary parameter	--	1.2223	.0027
		(.0035)	(.0002)
Log-likelihood	-188,523.53	-186,342.78	-188,387
AIC	377,151.1	372,791.6	376,880

Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.
Notes: Reference groups: [25-35) for the *Age group at hire*; female; 4 years of *Education* and skilled workers. All coefficients are statistically significant. Standard errors are shown in parentheses. AIC: Akaike information criterion. All models include *Industry*, *Region* and *Year* dummies. Number of observations: 422,738 observations. Number of failures: 64,239. Promotion events other than the first are not considered in this estimation.

Table 7: Accelerate Failure Time models' estimates: first promotion

Variables	Weibull (1)	Lognormal (2)	Log-logistic (3)	Generalized gamma (4)
Age group at hire				
[15,25)	-.0508	-.0494	-.0504	-.0509
	(.0082)	(.0089)	(.0086)	(.0086)
[35,45)	.0597	.0467	.0493	.0516
	(.0098)	(.0103)	(.0101)	(.0101)
[45,55)	.1048	.0853	.0928	.0939
	(.0132)	(.0136)	(.0135)	(.0134)
[55,75]	.2098	.1647	.1880	.1863
	(.0211)	(.0212)	(.0213)	(.0212)
Male	.0432	.0501	.0494	.0489
	(.0071)	(.0077)	(.0074)	(.0075)
Education				
No schooling	.2205	.1991	.2113	.2117
	(.0620)	(.0605)	(.0617)	(.0611)
2 years	.1096	.0832	.1016	.0972
	(.0426)	(.0422)	(.0428)	(.0424)
6 years	-.1524	-.1458	-.1534	-.1520
	(.0091)	(.0098)	(.0095)	(.0095)
9 years	-.2969	-.2759	-.2908	-.2882
	(.0107)	(.0115)	(.0112)	(.0112)
12 years	-.3891	-.3546	-.3769	-.3749
	(.0114)	(.0124)	(.0119)	(.0120)
15 years	-.4521	-.3920	-.4105	-.4180
	(.0292)	(.0317)	(.0302)	(.0306)
16 years	-.4870	-.4582	-.4770	-.4752
	(.0214)	(.0227)	(.0220)	(.0221)
Hierarchical level at hire				
Top managers	.2828	.2563	.2783	.2727
	(.0215)	(.0220)	(.0218)	(.0218)
Other managers	.2076	.2065	.2116	.2096
	(.0234)	(.0242)	(.0238)	(.0239)
Foremen/ supervisors	.1391	.0886	.1169	.1144
	(.0223)	(.0233)	(.0230)	(.0229)
Highly skilled	-.1218	-.0905	-.1233	-.1107
	(.0166)	(.0183)	(.0173)	(.0175)
Semi-skilled	-.1151	-.1061	-.1182	-.1130
	(.0102)	(.0109)	(.0106)	(.0106)
Unskilled	-.1708	-.1536	-.1714	-.1636
	(.0113)	(.0118)	(.0115)	(.0116)
Apprentices	-.3969	-.3675	-.3956	-.3894
	(.0095)	(.0107)	(.0100)	(.0101)
Firm size	-.2019	-.1824	-.1984	-.1950
	(.0024)	(.0025)	(.0024)	(.0025)
Constant	6.7462	6.4372	6.4237	6.6037
	(.0177)	(.0176)	(.0174)	(.0180)
Ancillary parameter	1.2223	1.3491	.7035	1.0901
	(.0029)	(.0038)	(.0021)	(.0071)
Kappa	--	--	--	.4644 (.0115)
Log-likelihood	-186,342.78	-186,064.71	-185,597.68	-185,341.33
AIC	372,791.6	372,235.4	371,301.4	370,790.7

Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005

Notes: Reference groups: [25-35) for the *Age group at hire*; female; 4 years of *Education* and skilled workers. All coefficients are statistically significant. Standard errors are shown in parentheses. AIC: Akaike information criterion. All models include *Industry*, *Region* and *Year* dummies. Number of observations: 422,738 observations. Number of failures: 64,239. Promotion events other than the first are not considered in this estimation.

Relating the Weibull model, that can be specified both in the PH and the AFT metric, with other AFT models like the lognormal, the log-logistic or the generalized gamma allows for the conclusion that the generalized gamma is the preferred model (showing the highest log-likelihood and the smallest AIC values). The generalized gamma is useful for testing model specification. Hence, a Wald test on the hypothesis that the shape parameter in the generalized gamma model is equal to 1 (or, in other words, a test on the appropriateness of the Weibull) is rejected (Chi-squared=2163.12, p-value=0). Also, the lognormal does not provide a satisfactory fit to the data since the hypothesis that the shape parameter in the generalized gamma model equals zero is rejected.

Coefficients on the categorical variable of interest *Age group at hire*, column (4) in Table 7, show that the time to first promotion increases with age: relative to the 25-34 reference age group, the survival times are lengthened by 5.2%, 9.4% and 18.6%, respectively, for the age groups 35-44, 45-54 and 55-75. Therefore, younger employees are promoted at a faster pace than less younger ones.

Another conclusion taken is that, compared to men, the time to first promotion is shortened by almost 5% for women. Also, the time to first promotion is reduced monotonically with the educational level: higher levels of education are associated with shorter survival times. McCue (1996) also reports a positive impact of education on the promotion hazard, but for all promotions not just the first one.

Results suggest that entering the firm at low levels of the hierarchy provides more opportunities for promotion which is consistent with the existence of internal labor markets (Baker *et al*, 1994a).

Finally, the firm size elasticity highlights the positive impact of the size on the promotion prospects: a 1% increase in firm size shortens by around 0.2% the survival time. Similar findings are presented by Pergamit and Veum (1999) and Francesconi (2001).

To account for unobserved heterogeneity, we also attempted to estimate the generalized gamma model with gamma or inverse-gaussian distributed frailty. However, convergence was not obtained in either case. Therefore, we retried the same procedure using the log-logistic model (which is the "second best" specification). The likelihood ratio test on the hypothesis that the overdispersion parameter equals zero presents a p-value of one. Thus, the frailty effect is not significant. Since the frailty variance is estimated to be near zero, the individual hazard function will resemble the population hazard function. In this situation, as Gutierrez (2002) suggests, the heterogeneity may be attributed to the passage of time. With the passage of time, the impact of the independent variables on the population hazard will diminish in favor of the frailty effect; for instance, gender (or other covariate) becomes less significant and the frailty gains relevance in determining the chance of promotion.

6.2 All promotions

As in the previous subsection, for a multiple event framework, we start by comparing the PH with the AFT metric to determine the model that best fits the data. Therefore, Table 8 shows the appropriateness of PH models while Table 9 presents AFT specifications.

New to these tables is the introduction of the variables *Previous events*, *Tenure* and *Tenure squared*, compared to the covariates present in Tables 6 and 7. The variable *Previous events* is included to account for event dependence as described in Section 5.3.

A concern using repeated events is that the hazard rate is expressed as a function of time since last event. Sometimes, it may be more adequate to let the hazard vary as a function of some common starting point. However, Allison (1984) refers that models for multiple events in which the hazard is a function of time since some fixed starting point may be inconvenient to estimate. As suggest by the author, to overcome this empirical inconvenience, we include in the model *Tenure* and its squared as independent variables. Also, its inclusion in the model intends to capture the influence of specific human capital accumulation and learning effects.

Again, Table 8 indicates that the Weibull is the preferred model in the PH form. Since the Weibull satisfies both the PH and the AFT assumptions, Table 9 displays Weibull model results in the AFT form together with the other AFT models. This allows for the comparison between models and it reveals that the log-logistic specification shows the highest log-likelihood and the lowest AIC value. Therefore, the log-logistic model is the preferred one and, for this reason, we will comment only on the results presented for this particular model.

Table 8: Proportional hazard models' coefficients

Variables	Exponential (1)	Weibull (2)	Gompertz (3)
Age group at hire			
[15,25)	.0003†	-.0109†	-.0034†
	(.0084)	(.0084)	(.0084)
[35,45)	-.0290	-.0146†	-.0117†
	(.0102)	(.0102)	(.0102)
[45,55)	-.0670	-.0624	-.0635
	(.0137)	(.0137)	(.0137)
[55,75]	-.2127	-.2075	-.1926
	(.0229)	(.0229)	(.0229)
Male	-.0468	-.0600	-.0564
	(.0073)	(.0073)	(.0073)
Education			
No schooling	-.2131	-.2494	-.2570
	(.0624)	(.0625)	(.0626)
2 years	-.1963	-.1777	-.1602
	(.0450)	(.0450)	(.0450)
6 years	.0912	.1218	.1317
	(.0093)	(.0093)	(.0093)
9 years	.1580	.2185	.2193
	(.0112)	(.0112)	(.0112)
12 years	.2629	.3257	.3284
	(.0118)	(.0119)	(.0118)
15 years	.2460	.3088	.3161
	(.0304)	(.0304)	(.0304)
16 years	.2332	.3041	.3196
	(.0228)	(.0228)	(.0228)
Hierarchical level at hire			
Top managers	-.1794	-.2178	-.2070
	(.0235)	(.0245)	(.0234)
Other managers	-.0978	-.1166	-.1141
	(.0248)	(.0248)	(.0248)
Foremen/ supervisors	-.0127†	-.0458	-.0429
	(.0233)	(.0233)	(.0233)
Highly skilled	.1869	.1713	.1832
	(.0175)	(.0175)	(.0175)
Semi-skilled	.1054	.1231	.1160
	(.0105)	(.0105)	(.0105)
Unskilled	.1012	.1426	.1295
	(.0116)	(.0116)	(.0116)
Apprentices	.3043	.3257	.3195
	(.0095)	(.0095)	(.0095)
Previous events	.6088	.7391	.7693
	(.0038)	(.0036)	(.0037)
Tenure	-.0118	-.0407	-.0236
	(.0003)	(.0003)	(.0003)
Tenure squared x 10^{-2}	-.0037	.0068	-.0043
	(.0002)	(.0002)	(.0002)
Firm size	.1600	.1752	.1682
	(.0023)	(.0024)	(.0023)
Constant	-5.8953	-7.7968	-6.1421
	(.0189)	(.0224)	(.0190)
Ancillary parameter	--	1.7812	.0271
		(.0023)	(.0002)
Log-likelihood	-238,714.73	-220,292.33	-229,505.04
AIC	477,539.5	440,696.7	459,122.1

Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.

Notes: Reference groups: [25-35) for the *Age group at hire*; female; 4 years of *Education* and skilled workers. All coefficients are statistically significant with the exception of those signalled with †. Standard errors are shown in parentheses. AIC: Akaike information criterion. All models include *Industry*, *Region* and *Year* dummies. Number of observations: 479,308 observations. Number of failures: 91,214.

Table 9: Accelerate Failure Time models' estimates

Variables	Weibull (1)	Lognormal (2)	Log-logistic (3)	Generalized gamma (4)
Age group at hire				
[15,25)	.0061†	.0001†	-.0021†	.0013†
	(.0047)	(.0051)	(.0045)	(.0048)
[35,45)	.0082†	.0161	.0167	.0148
	(.0057)	(.0059)	(.0053)	(.0056)
[45,55)	.0350	.0363	.0381	.0375
	(.0077)	(.0078)	(.0071)	(.0075)
[55,75]	.1165	.1039	.1079	.1127
	(.0129)	(.0124)	(.0115)	(.0122)
Male	.0337	.0279	.0264	.0291
	(.0041)	(.0044)	(.0039)	(.0041)
Education				
No schooling	.1400	.1532	.1423	.1451
	(.0337)	(.0348)	(.0322)	(.0340)
2 years	.0998	.1097	.1123	.1089
	(.0252)	(.0247)	(.0230)	(.0242)
6 years	-.0684	-.0504	-.0451	-.0542
	(.0052)	(.0056)	(.0050)	(.0053)
9 years	-.1227	-.0850	-.0798	-.0951
	(.0063)	(.0066)	(.0059)	(.0063)
12 years	-.1829	-.1392	-.1296	-.1513
	(.0066)	(.0071)	(.0063)	(.0067)
15 years	-.1734	-.1185	-.1138	-.1355
	(.0171)	(.0182)	(.0160)	(.0171)
16 years	-.1707	-.1162	-.1109	-.1318
	(.0128)	(.0132)	(.0118)	(.0126)
Hierarchical level at hire				
Top managers	.1223	.0634	.0824	.0911
	(.0132)	(.0129)	(.0118)	(.0126)
Other managers	.0655	.0383	.0476	.0523
	(.0139)	(.0139)	(.0127)	(.0135)
Foremen/ supervisors	.0257	-.0119†	-.0026†	.0053†
	(.0131)	(.0133)	(.0121)	(.0128)
Highly skilled	-.0961	-.0638	-.0670	-.0762
	(.0098)	(.0106)	(.0093)	(.0100)
Semi-skilled	-.0691	-.0444	-.0453	-.0537
	(.0059)	(.0062)	(.0055)	(.0065)
Unskilled	-.0800	-.0439	-.0479	-.0552
	(.0065)	(.0068)	(.0061)	(.0065)
Apprentices	-.1828	-.1560	-.1568	-.1699
	(.0054)	(.0059)	(.0052)	(.0055)
Previous events	-.4149	-.5639	-.5454	-.4939
	(.0022)	(.0030)	(.0027)	(.0027)
Tenure	.0228	.0291	.0295	.0265
	(.0002)	(.0002)	(.0002)	(.0002)
Tenure squared $\times 10^{-2}$	-.0038	-.0071	-.0071	-.0054
	(.0001)	(.0001)	(.0001)	(.0001)
Firm size	-.0984	-.0864	-.0848	-.0911
	(.0013)	(.0014)	(.0013)	(.0013)
Constant	4.3773	4.0048	3.8266	4.1227
	(.0113)	(.0118)	(.0110)	(.0117)
Ancillary parameter	1.7812	.8930	.4388	.6948
	(.0045)	(.0023)	(.0013)	(.0031)
Kappa	--	--	--	.5184 (.0073)
Log-likelihood	-220,292.33	-220,046.37	-216,118.36	-217,950.62
AIC	440,696.7	440,204.7	432,348.7	436,015.2

Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.

Notes: Reference groups: [25-35) for the *Age group at hire*; female; 4 years of *Education* and skilled workers. All coefficients are statistically significant with the exception of those signalled with †. Standard errors are shown in parentheses. AIC: Akaike information criterion. All models include *Industry*, *Region* and *Year* dummies. Number of observations: 479,308 observations. Number of failures: 91,214.

Relative to younger workers, aged 25 to 34 at hire (the reference group), workers hired at older ages face longer times to promotion. In effect, column (3) in Table 9 shows that workers aged 35 to 44 at hire experience a 1.7% higher survival time than the reference group. Also, survival times monotonically increase with age at hire. Compared to employees hired at ages 25 to 34, workers in the 45 to 54 age group and those in the 55 to 75 years cohort at hire present longer times to promotion (3.8% and 10.8%, respectively). These results suggest that firms seem to favor younger workers in promotions. Stronger effects were obtained when considering the distribution of time to first promotion. This preference in promotion opportunities towards younger employees may influence older workers' motivation as well as their employment status. Effectively, evidence shows that age discrimination practices at the firm level are consistent with lower wage growth for older workers, with early retirement behavior and job separations (Adams, 2002; Johnson and Neumark, 1997).

Considering gender, men are found to have a 2.6% higher survival time than women, meaning that women are more likely to receive a promotion than men. Ferreira (2009), using the same data set, reports similar results for overall promotions.

Better educated individuals see their survival times to promotion shortened. This is consistent with the returns to education associated with human capital theory. However, if education can be considered an indicator of general human capital accumulation, tenure may also be regarded as a characteristic of specific human capital accumulation and of learning. Results suggest that time to promotion increases with tenure but at a decreasing rate. McCue (1996) finds a similar result regarding the effect of tenure on the promotion hazard.

Considering the *Hierarchical level at hire*, estimates show that compared to employees hired as skilled workers, those getting into the firm at lower hierarchical levels (apprentices, unskilled and semi-skilled workers) experience shorter times to promotion. Nevertheless, although at a higher hierarchical level, highly skilled workers also present a 6.7% smaller survival time in comparison with skilled workers at hire.

The occurrence dependence variable *Previous events* clearly suggests that past promotions are a stronger indicator of subsequent ones. Previous promotions contribute to significantly shorten survival times: the receipt of one (previous) promotion reduces by 54.5% the time to promotion. Thus, previously promoted workers are more likely to be promoted once again which is consistent with the promotion fast-tracks documented in the literature (Baker *et al.*, 1994a; Pergamit and Veum, 1999).

As for firm characteristics, *Firm size* is negatively associated with survival times, as the elasticity of the survival time relative to the number of firm employees presents a negative sign. Workers in large firms face shorter periods to promotion than those in small firms. Firms with a larger workforce have overall structured hierarchical levels that open to the set of an internal labor market. In the existence of an internal labor market, medium to high levels of the hierarchy are filled in through promotions from lower levels. This result is in agreement with previous empirical findings (Pergamit and Veum, 1999; Francesconi, 2001).

Table 10 shows the results for log-logistic models with frailty and shared frailty. Columns (1) and (2) report the estimates for the frailty models with gamma and inverse-gaussian distribution for the frailty, respectively. Comparing these with the results presented in Table 9 for the log-logistic model no striking differences occur: coefficients are very similar in each of the models. Nonetheless, the frailty effect is always statistically significant considering the results of the likelihood ratio tests.

The model that best fits the data is the one with the gamma distributed frailty and it is also the preferred model because it has the lowest AIC value. This is the reason why in the shared-frailty models we use the gamma distribution for the frailty.

In a shared-frailty model, the frailty is specific to a particular group. Columns (3), (4) and (5) in Table 10 present the estimates for models where the frailty is shared by the match worker/firm, by the worker and by the firm, respectively. The results of columns (3) and (4) do not differ substantially and both are similar to the results obtained for a non-frailty specification. The major difference occurs when allowing for correlation within firms. In effect, considering the overall specifications, the one that uses a frailty shared at the firm level is the one producing the best fit (it presents the largest log-likelihood and the smallest AIC value).

Table 10: Estimates from the log-logistic models with frailty

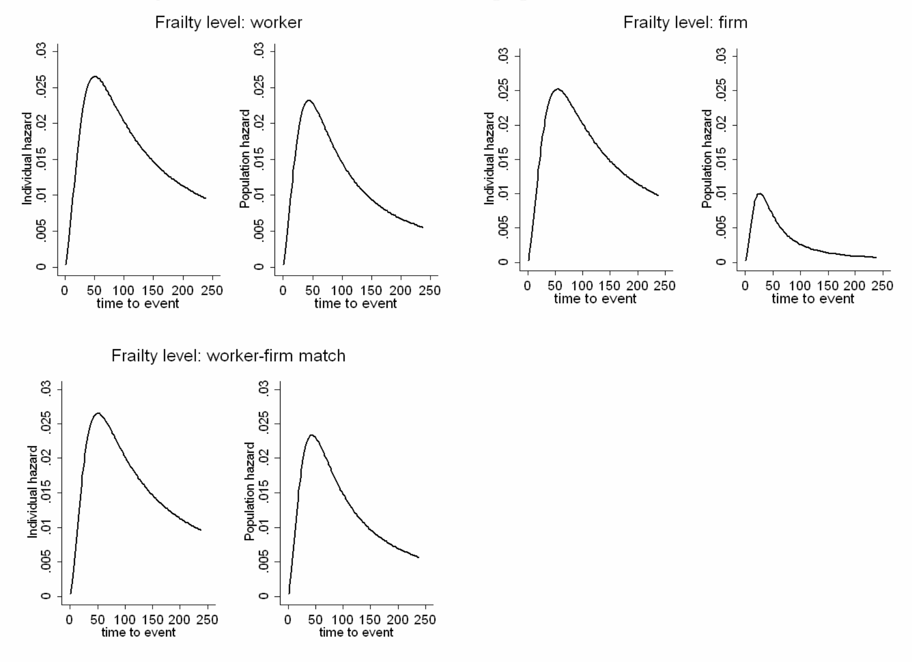
Variables	Frailty		Shared-frailty (Gamma)		
	Gamma	Inverse gaussian	Match	Worker	Firm
	(1)	(2)	(3)	(4)	(5)
Age group at hire					
[15,25)	-.0025†	-.0024†	-.0029†	-.0030†	-.0132
	(.0045)	(.0045)	(.0046)	(.0046)	(.0044)
[35,45)	.0168	.0168	.0173	.0175	.0227
	(.0053)	(.0053)	(.0054)	(.0054)	(.0052)
[45,55)	.0381	.0381	.0384	.0386	.0517
	(.0071)	(.0071)	(.0072)	(.0072)	(.0071)
[55,75]	.1064	.1067	.1066	.1068	.1357
	(.0114)	(.0114)	(.0116)	(.0116)	(.0114)
Male	.0260	.0261	.0255	.0256	.0430
	(.0039)	(.0039)	(.0040)	(.0040)	(.0044)
Education					
No schooling	.1420	.1422	.1466	.1474	.0370†
	(.0320)	(.0320)	(.0327)	(.0328)	(.0326)
2 years	.1105	.1109	.1131	.1132	.0177†
	(.0229)	(.0229)	(.0233)	(.0234)	(.0241)
6 years	-.0440	-.0443	-.0440	-.0439	-.0141
	(.0050)	(.0050)	(.0051)	(.0051)	(.0052)
9 years	-.0775	-.0780	-.0772	-.0768	-.0334
	(.0059)	(.0059)	(.0060)	(.0061)	(.0063)
12 years	-.1260	-.1268	-.1252	-.1248	-.0169
	(.0063)	(.0063)	(.0064)	(.0065)	(.0068)
15 years	-.1095	-.1104	-.1075	-.1068	-.0203†
	(.0160)	(.0160)	(.0163)	(.0163)	(.0154)
16 years	-.1075	-.1082	-.1072	-.1066	-.0283
	(.0118)	(.0118)	(.0120)	(.0120)	(.0124)
Hierarchical level at hire					
Top managers	.0791	.0797	.0767	.0761	.0949
	(.0118)	(.0118)	(.0120)	(.0120)	(.0121)
Other managers	.0461	.0464	.0451	.0444	.0960
	(.0127)	(.0127)	(.0129)	(.0129)	(.0127)
Foremen/ supervisors	-.0043†	-.0039†	-.0052†	-.0060†	-.0024†
	(.0121)	(.0121)	(.0123)	(.0123)	(.0119)
Highly skilled	-.0638	-.0644	-.0641	-.0642	.0699
	(.0093)	(.0093)	(.0094)	(.0095)	(.0096)
Semi-skilled	-.0433	-.0437	-.0424	-.0424	.0078†
	(.0055)	(.0055)	(.0056)	(.0057)	(.0060)
Unskilled	-.0458	-.0462	-.0456	-.0454	.0148
	(.0060)	(.0060)	(.0062)	(.0062)	(.0068)
Apprentices	-.1534	-.1541	-.1566	-.1565	-.1031
	(.0052)	(.0052)	(.0053)	(.0053)	(.0054)
Previous events	-.5593	-.5566	-.5227	-.5202	-.2521
	(.0030)	(.0029)	(.0035)	(.0036)	(.0025)
Tenure	.0301	.0300	.0301	.0302	.0290
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
Tenure squared $\times 10^{-2}$	-.0076	-.0075	-.0075	-.0075	-.0082
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Firm size	-.0833	-.0836	-.0845	-.0845	.0021†
	(.0013)	(.0013)	(.0013)	(.0013)	(.0034)
Constant	3.7815	3.7900	3.7957	3.7934	3.5514
	(.0115)	(.0114)	(.0112)	(.0112)	(.0150)
Ancillary parameter	.4291	.4308	.4306	.4301	.4231
	(.0014)	(.0014)	(.0013)	(.0013)	(.0013)
Overdispersion parameter	.1119	.0961	.1768	.1902	3.5156
	(.0098)	(.0101)	(.0115)	(.0117)	(.0503)
Log-likelihood	-216,037.94	-216,054.8	-215,849	-215,819.67	-175,232.38
AIC	432,189.9	432,223.6	431,812	431,753.3	350,578.8
Number of groups	--	--	422,738	402,463	44,728

Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.

Notes: Reference groups: [25-35) for the *Age group at hire*; female; 4 years of *Education* and skilled workers. All coefficients are statistically significant with the exception of those signalled with †. Standard errors are shown in parentheses. AIC: Akaike information criterion. All models include *Industry*, *Region* and *Year* dummies. Number of observations: 479,308 observations. Number of failures: 91,214.

Figure 4 shows the estimated individual and population hazard functions for the three different levels of frailty.

Figure 4: Estimated individual and population hazard functions



Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.
Note: 'Time to event' measures the time to promotion, in months.

When the frailty is significant, the population hazard will tend to begin falling past a certain time, independently of the shape of the individual hazard. This is explained by the frailty effect: with the passage of time, the frailer individuals will fail and only the less frail will remain in the population hence generating a more homogeneous population. This is reflected in Figure 4.

The stronger firm frailty effect shows that firms' unobservable characteristics are relevant in the determination of the promotion process. Controlling for firms' unobservable heterogeneity, the magnitude of the impact of the *Age group at hire* on the time to promotion is even stronger. Within firms, compared to workers hired with 25 to 34 years old, when workers are hired above the age 34 threshold they find their time to promotion lengthened and this length is amplified with age: workers aged 35 to 44 at hire experience a 2.3% higher survival time than the reference group, with times to promotion enhanced to 5.2% and 13.6%, respectively, for workers aged 45 to 54 and older than 55.

Overall results[11] suggest that older individuals have less promotion opportunities than younger workers, controlling for firm, worker or match effects.

7 Conclusion

Using a sample of new firms and their workers, this research shows that age harms workers' promotion opportunities. Duration models' results suggest that older individuals experience longer survival times to promotion than their younger counterparts. The magnitude of this effect is even stronger when considering just the time to first promotion. Older employees are left for last in promotion.

Facing uneven promotion prospects, older employees may face discouragement in the workplace, less appreciation and become more attracted by early retirement schemes.

These results seem to demonstrate that active aging policies should be more focused at endorsing labor market opportunities for older workers. If the aim is to delay the exit from the labor force, in order to raise the employment rate of older workers, then attention must be given to the improvement of older individuals' chances in all employment related dimensions.

Left for future research is the analysis on how the employment history of older individuals influences their future career development. That is, knowing if older workers entering new firms are "job changers" or individuals that come from a spell of non-employment should have an impact on their promotion prospects. Moreover, the study of how uneven promotion opportunities influence the labor market outcomes of older workers, with particular interest on the exit decision, remains a topic for future research. This can be tested within a competing risks framework in which retirement is one of the alternative paths. Knowing the factors that influence the decision of leaving the labor force is crucial for the development of policy measures that aim at postponing the exit from the labor market.

[11] We have also estimated the models for a sample of workers aged 15 to 65, since 65 is the legal retirement age in Portugal. Nevertheless, results remain the same: older workers experience greater times to promotion than younger workers do.

References

Abraham, Katharine G. and James L. Medoff (1985) "Length of service and promotions in union and nonunion work groups." *Industrial and Labor Relations Review*, 38(3): 408-420.

Adams, Scott (2002) "Passed over for promotion because of age: an empirical analysis of the consequences." *Journal of Labor Research*, 23(3): 447-461.

Allison, Paul D. (1984) *Event History Analysis: Regression for Longitudinal Event Data.* Sage University Paper Series on Quantitative Applications in the Social Sciences, series no. 07-046. Beverly Hills, CA: Sage.

Baker, George, Michael Gibbs and Bengt Holmstrom (1994a) "The internal economics of the firm: evidence from personnel data." *Quarterly Journal of Economics*, 109(4): 881-919.

Baker, George, Michael Gibbs and Bengt Holmstrom (1994b) "The wage policy of a firm." *Quarterly Journal of Economics*, 109(4): 921-955.

Baker, George and Bengt Holmstrom (1995) "Internal labor markets: too many theories, too few facts." *American Economic Review*, 85(2): 255-259.

Becker, Gary S. (1962) "Investment in human capital: a theoretical analysis." *Journal of Political Economy*, 70(5): 9-49.

Bernhardt, Dan and David Scoones (1993) "Promotion, turnover and preemptive wage offers." *American Economic Review*, 83(4): 771-791.

Blank, Rebecca M. (1988) "Simultaneously modeling the supply of weeks and hours of work among female household heads." *Journal of Labor Economics*, 6(2): 177-204.

Booth, Alison L., Marco Francesconi and Jeff Frank (2003) "A sticky floors model of promotion, pay and gender." *European Economic Review*, 47: 295-322.

Cameron, Colin A. and Pravin K. Trivedi (2005) *Microeconometrics methods and applications*. Cambridge University Press: Cambridge.

Carmichael, Lorne (1983) "Firm-specific human capital and promotion ladders." *Bell Journal of Economics*, 14(1): 251-258.

Chan, William (1996) "External recruitment versus internal promotion." *Journal of Labor Economics*, 14(4): 555-570.

Daniel, K. and J. Heywood (2007) "The determinants of hiring older workers: UK evidence." *Labour Economics*, 14(1), 35-51.

European Commission (2008) *Employment in Europe 2008*. Office for Official Publications of the European Communities: Luxembourg.

Farber, Henry S. and Robert Gibbons (1996) "Learning and wage dynamics." *Quarterly Journal of Economics*, 111(4): 1007-1047.

Ferreira, Priscila (2009) "The determinants of promotions and firm separations." ISER Working Paper Series no. 2009-11.

Francesconi, Marco (2001) "Determinants and consequences of promotions in Britain." *Oxford Bulletin of Economics and Statistics*, 63(3): 279-310.

Gibbons, Robert (1996) "Incentives and careers in organizations." NBER Working Paper 5705.

Gibbons, Robert and Michael Waldman (1999) "A theory of wage and promotion dynamics inside firms." *Quarterly Journal of Economics*, 114(4): 1321-1358.

Gibbons, Robert and Michael Waldman (2006) "Enriching a theory of wage and promotion dynamics inside firms." *Journal of Labor Economics*, 24(1): 59-107.

Gutierrez, Roberto (2002) "Parametric frailty and shared frailty survival models." *Stata Journal*, 2(1): 22-44.

Heywood, J.; L.-S. Ho and X. Wei (1999) "The determinants of hiring older workers: evidence from Hong Kong." *Industrial and Labor Relations Review*, 52(3), 444-459.

Hirsch, Barry T. (2005) "Why do part-time workers earn less? The role of worker and job skills." *International and Labor Relations Review*, 58(4): 525-551.

Hutchens, Robert (1986) "Delayed payment contracts and a firm's propensity to hire older workers." *Journal of Labor Economics*, 4(4), 439-457.

Hutchens, Robert (1988) "Do job opportunities decline with age?" *Industrial and Labor Relations Review*, 42(1), 89-99.

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

Johnson, Richard W. and David Neumark (1997) "Age discrimination, job separations, and employment status of older workers: evidence from self-reports." *Journal of Human Resources*, 32(4): 779-811.

Jovanovic, Boyan (1979) "Job matching and the theory of turnover." *Journal of Political Economy*, 87(5): 972-990.

Lazear, Edward P. (1979) "Why is there mandatory retirement?" *Journal of Political Economy*, 87(6): 1261-1284.

Lazear, Edward P. (1981) “Agency, earnings profiles, productivity, and hours restrictions.” *American Economic Review*, 71(4): 606-620.

Lazear, Edward P. (1999) “Personnel economics: past lessons and future directions. Presidential address to the Society of Labor Economists, San Francisco, May 1, 1998.” *Journal of Labor Economics*, 17(2): 199-236.

Lazear, Edward P. and Sherwin Rosen (1981) “Rank-order tournaments as optimum labor contracts.” *Journal of Political Economy*, 89(5): 841-864.

Lazear, Edward P. and Sherwin Rosen (1990) “Male-female wage differentials in job ladders.” *Journal of Labor Economics*, 8(1), part 2: S106-S123.

Lima, Francisco (2004) “How much mobility? Careers, promotions, and wages.” CEG-IST Research paper no. 3/2004.

Lima, Francisco and Mário Centeno (2003) “The careers of top managers and firm openness: internal versus external labour markets.” Banco de Portugal, Economic Research Department, WP 15-03.

Lima, Francisco and Pedro Telhado Pereira (2003) “Careers and wages within large firms: evidence from a matched employer-employee data set.” *International Journal of Manpower*, 24(7): 812-835.

Manove, Michael (1997) “Job responsibility, pay and promotion.” *Economic Journal*, 107(440): 85-103.

Mata, José and Pedro Portugal (1994) “Life duration of new firms.” *Journal of Industrial Economics*, 42(3): 227-245.

McCue, Kristin (1996) “Promotions and wage growth.” *Journal of Labor Economics*, 14(2): 175-209.

Oi, Walter (1962) “Labor as a quasi-fixed factor.” *Journal of Political Economy, 70*(6), 538-555.

Olson, Craig A. and Brian E. Becker (1983) “Sex discrimination in the promotion process.” *Industrial and Labor Relations Review*, 36(4): 624-641.

Patel, Katie, Richard Kay and Lucy Rowell (2006) “Comparing proportional hazards and accelerated failure time models: an application in influenza.” *Pharmaceutical Statistics*, 5: 213-224.

Pergamit, Michael R. and Jonathan R. Veum (1999) “What is a promotion?” *Industrial and Labor Relations Review*, 52(4): 581-601.

Portugal. Ministry of Labor and Social Solidarity (1986-2005) Quadros de Pessoal. Data in magnetic medium.

Rosen, Sherwin (1982) "Authority, control, and the distribution of earnings." *Bell Journal of Economics*, 13(2): 311-323.

Rosen, Sherwin (1986) "Prizes and incentives in elimination tournaments." *American Economic Review*, 76(4): 701-715.

Sattinger, Michael (1975) "Comparative advantage and the distributions of earnings and abilities." *Econometrica*, 43(3): 455-468.

Silva, António Dias and Bas van der Klaauw (2006) "Wage dynamics and promotions inside and between firms." IZA DP no. 2351.

Stata (2007) *Stata survival analisys and epidemiological table reference manual.* Release 10. Stata Press: College Station, Texas.

Topel, Robert H. and Michael P. Ward (1992) "Job mobility and the careers of young men." *Quarterly Journal of Economics*, 107(2): 439-479.

Van Bastelaer, Alois, Georges Lemaître and Pascal Marianna (1997) "The definition of part-time work for the purpose of international comparisons." *OECD Labour Market and Social Policy Occasional Papers*, No. 22, OECD Publishing.

Waldman, Michael (1984a) "Worker allocation, hierarchies and the wage distribution." *Review of Economic Studies*, 51(1): 95-109.

Waldman, Michael (1984b) "Job assignment, signalling, and efficiency." *RAND Journal of Economics*, 15(2): 255-267.

Appendices

Appendix A Construction of the sample

To get the sample used in the study we started by creating a panel of firms merging the cross-sectional 1986 to 2005 files available on *Quadros de Pessoal*. The aim was to obtain a panel including just new firms. Thus, the variable *Year of Creation* available on each cross-sectional file for firms is crucial.

From the above panel we started by eliminating the firms reporting two or more different years of creation (4% of the observations dropped), to avoid misinterpretations. After identifying the year in which the firm firstly appears in the dataset and signalling the moment when the firm is created, we kept the firms for which the year of creation coincides with the first year of appearance in the dataset (Panel A).

Next, we turned our attention to the workers' panel. In situations where there existed more than one observation for worker/year we kept just the observation related to the main job (the one with higher reported hours of work). Workers with 30[12] or less hours/week of work were removed from the sample. This was done in order to assure some attachment to the labor market. Also we kept just employees aged 15 to 75[13]. A relevant variable in this panel is the *Date of Admission at the Firm* since it is used to create the *Promotion* indicator as well as the *Tenure* variable. Therefore, we checked for inconsistencies in the variable such as: *Date of Admission* higher than the year of the survey. Also, if the reported *Date of Admission* for the pair worker/firm was always the same, missing values on *Date of Admission* for that pair were replaced by the reported non-missing value. We have also replaced inconsistencies (like decreasing *Date of Admission* over time) with the value reported more than half of the times. The remaining inconsistencies and missing values on this variable were dropped (Panel B).

Afterwards, sorted by firm and year, we merged Panel A with Panel B obtaining a panel of new firms and their workers. Firms that did not present information on workers from the year of creation and firms that had workers hired (*Date of Admission*) before the year of creation were excluded. Finally, we have included firms with more than two years of

[12] In Van Bastelaer *et al.* (1997) a definition of part-time work is presented for international comparison. In some countries, like the United States, 35 hours of work a week is the normal threshold for a worker to be classified as a part-timer. That is the benchmark in the papers by Blank (1988) and Hirsch (2005). In other countries, like the United Kingdom, working 30 or fewer hours per week is the boundary in the definition of part-time employment. I consider this 30 hours threshold to define part-time employment in Portugal.
[13] For comparison, in the empirical analysis we have also used a subsample of workers aged 15 to 65.

survival in the market. The above exclusions resulted in a sample with 1,033,767 observations, for 416,170 workers, 44, 920 firms and 437,498 spells firm/worker.

Appendix B Tables

Table B1: Distribution of firms' survival times

Number of years of survival	Frequency	Percent
3	9,407	20.94
4	9,685	21.56
5	2,285	5.09
6	5,231	11.64
7	3,941	8.77
8	3,530	7.86
9	2,862	6.37
10	2,245	5.00
>10	5,734	12.77
Total	44,920	100

Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.

Table B2: Distribution of promotions

Number of promotions	Frequency	Percent
0	352,473	84.69
1	46,158	11.09
2	11,817	2.84
3	3,619	.87
4	1,255	.30
5	470	.11
6	204	.05
7	85	.02
8	36	.01
9	32	.01
10	7	.00
11	6	.00
12	3	.00
13	2	.00
14	1	.00
15	2	.00
Total	416,170	100

Source: Computations from the authors based on *Quadros de Pessoal*, 1986-2005.

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