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Technology, skills and job separation

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Abstract

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The increased relative demand for skills brought by skill-biased technical change has been considered as an important explanation for the growth in the wage differential between skilled and unskilled workers, despite the increase in the supply of skills.

Most technical change is considered to favor skilled workers because new technologies generally require more skills and education, and because educated and skilled workers have a relative advantage in the implementation of new technology (Doms, Dunne, and Troske 1997).

The skill-biased technical change literature has mostly focused on the skill premium regarding wages and how the

premium changes with technological progress. While the impact on wages is important, technical change also has consequences in other aspects of the labor market such as job duration and separation rates. On these implications, research efforts have not been as profound but still some contributions can be found throughout the literature (for example Bartel and Sicherman 1993).

As far as we can tell, there are no works that study the technology-skill complementarity effect on the hazard of job separation and how this hazard changes with tenure. The present work aims at filling this gap.

Farber (1994) establishes that the hazard of a job ending decreases with tenure. This may be explained by accumulation of specific human capital. In the literature, we can find evidence that more technology demands more specific human capital, mostly in the form of on-the-job training (Lillard and Tan 1986). Griliches (1969) proposed that capital (including technology) and skills are complements, in that capital increases the productivity of skilled workers relatively more than it does to unskilled workers's productivity. Under the hypothesis of technology-skill complementarity, we expect specific human capital to be valued more in more technological industries. As a consequence, the more intense the technology usage is, the smaller the hazard of job separation will be because of accumulation of specific human capital.

General human capital, in the form of formal education, also plays a role in determining separation rates. More educated workers are more skilled, and so they will be more productive than less-educated workers. If technology and skills are complementary, we expect the education premium to be larger in more technology intense industries.

We rely on the Quadros de Pessoal, an extensive longitudinal matched employer-employee data set containing every private firm in Portugal with at least one paid employee. It includes detailed information on workers and firms and allows for the mapping of workers's job-to-job flows.

To understand how technological intensity influences the effect that different measures of skills and specific human capital have on the hazard of job separation, we used different specifications of discrete-time proportional hazards models with unobserved heterogeneity and applied them to three technological intensity categories - high, medium and low intensity.

Our results show that complementarity between technology and skills is observed in terms of turnover. Specifically, more educated workers have lower hazards of separation in every technological category and the education premium on the hazard is higher the more intense the usage of technology is. Using other, more specific, measures of skills we find more skilled workers face lower hazards and skills have a higher impact on separation the more technology is used. Finally, the results suggest specific human capital plays a stronger role than general human capital in determining the hazard of job separation and its value is larger in more technological industries.

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1. Introduction

The increased relative demand for skills brought by skill-biased technical change has been considered as an important explanation for the growth in the wage differential between skilled and unskilled workers, despite the increase in the supply of skills. Most technical change is considered to favor skilled workers because new technologies generally require more human capital, and because educated and skilled workers have a relative advantage in the implementation of new technologies (Doms, Dunne, and Troske 1997). The skill-biased technical change literature has mostly focused on the skill premium regarding wages and how the premium changes with technological progress. While the impact on wages is important, technical change also has consequences in other features of the labor market such as job duration and separation rates.

Understanding how separation rates vary with technological intensity is important in at least three ways. At the policy level, the knowledge about the relationship between the use of technology and the prevalence of certain patterns of job stability helps to identify the necessity of policy interventions. At the firm level, it will help firms to understand what makes a worker stay longer and inform human resource practices to retain ablest workers. Finally, workers' decisions concerning skill acquisition, schooling or training, or concerning job search in a particular industry will also be influenced by the perspectives of finding a better match with higher chances of surviving.

There are several empirical studies that find job duration is influenced by both worker and firm characteristics.¹ However, research efforts on the implications of technology on job duration have not been as profound, but still some contributions can be found throughout the literature (for example, Bartel and Sicherman 1993; Boockmann and Steffes 2010). As far as we can tell, there are no works that study the technology-skill complementarity effect on

¹ See, for example, Bellman, Bender, and Hornsteiner (2000) and Boockmann and Steffes (2010) for the German case; Booth, Francesconi, and García-Serrano (1999) for the UK; Diebold, Polsky, and Neumark (1997) for the USA; and Horny, Mendes, and van den Berg (2012) for the Portuguese case.

the hazard of job separation and how this hazard changes with tenure. The present work aims at filling this gap.

Farber (1994) establishes that the hazard of a job ending decreases with tenure. This may be explained by accumulation of specific human capital. In the literature, we can find evidence that more technology demands more specific human capital, mostly in the form of on-the-job training (Lillard and Tan 1986). Griliches (1969) proposed that capital (including technology) and skills are complements, in that capital increases the productivity of skilled workers relatively more than it does to unskilled workers' productivity. Under the hypothesis of technology-skill complementarity, we expect specific human capital to be valued more in more technological intense industries, inducing smaller hazards of job separation.

General human capital, in the form of formal education, also plays a role in determining separation rates. More educated workers are more skilled, and so they will be more productive than less-educated workers. If technology and skills are complementary, we expect the education premium to be larger in more technology intense industries.

To understand how technological intensity influences the effect that different measures of skills and specific human capital have on the hazard of job separation, we used different specifications of discrete-time proportional hazards models with unobserved heterogeneity and applied them to three technological intensity categories derived from OECD's classification — high, medium and low intensity. We use *Quadros de Pessoal*, an extensive longitudinal matched employer-employee data set containing every private firm in Portugal with at least one paid employee. It includes detailed information on workers and firms and allows for the mapping of workers' job-to-job flows.

Our results show that complementarity between technology and skills is observed in terms of turnover. More educated workers have lower hazards of separation in every technological category and the education premium on the hazard is higher the more intense the usage of technology is. Using other, more specific, measures of skills we find that more skilled workers face lower hazards and skills have a higher impact on separation the more technology is

used. Finally, the results suggest specific human capital plays a stronger role than general human capital in determining the hazard of job separation and its value is larger in more technological industries.

2. Technology and skills-premium

The increased relative demand for skills brought by skill-biased technical change has been considered an important explanation for the growth in the wage differential between skilled and unskilled workers, despite the increase in the supply of skills (Acemoglu 2002), and has been observed across the developed world (Berman, Bound, and Griliches 1994; Berman, Bound, and Machin 1998). Most technical change is considered to favor skilled workers because usage of new technologies generally requires more skills and education (Doms, Dunne, and Troske 1997), and educated and skilled workers have a relative advantage in the implementation of new technology (Nelson and Phelps 1966; Welch 1970; Bartel and Lichtenberg 1987; Greenwood and Yorukoglu 1997). Furthermore, Griliches (1969) proposed that capital (including technology) and skills are (relative) complements, in that capital increases the productivity of skilled workers relatively more than it does to unskilled workers' productivity. Evidence of technology-skill complementarity goes back to at least the beginning of the 20th century (Goldin and Katz 1998).

The skill-biased technical change literature has mostly focused on the skill premium regarding wages and how the premium changes with technological progress.² For example, Dunne and Schmitz (1995) found that plants using advanced technology employed relatively more non-production workers (usually considered more skilled) and paid higher wages; Autor, Katz and Krueger (1998) reveal a positive correlation between computer use by workers and wages; Allen (2001) finds that, in industries going through more technological change, wage differentials by schooling increased and experienced workers saw their wages growing faster than their counterparts in less technological sectors. Finally, Bound and Johnson (Bound and Johnson 1992) settle

² See Acemoglu (2002) for a more extensive review on the implications of technological progress on the labor market.

that changes in wage structure observed during the 1980's were caused by skill-biased technical change.

Opposing the idea of skill-biased technical change, Bartel and Sicherman (1999) suggest that while higher wages are paid in high-tech industries, this is not because of technological change per se but because more skilled workers sort themselves into those industries, thus commanding higher wages.

While the impact on wages is important, technical change also has consequences in other aspects of the labor market such as job duration, separation rates, worker mobility and turnover. On these implications, research efforts have not been as profound but still some contributions can be found throughout the literature. For example, Bartel and Sicherman (1993) estimate the likelihood of retirement of older workers and find that those in industries with high rates of technological change will retire later if this change does not make their human capital obsolete. Also, Greenhalgh and Mavrotas (1996) find that R&D is associated with more training and less mobility for men, but do not explicitly control for job duration.

Pacelli, Rapiti and Revelli (1998) present some evidence that companies that invest in R&D have smaller separation rates. However, their conclusion is far from clear-cut, possibly because of endogeneity caused by including wages in their model. Whilst they find that separation rates are smaller for workers with long spells, the authors only distinguish between workers with spells longer than twelve months and workers with spells shorter than that. Boockmann and Steffes (2010) use duration models to estimate the hazard of job separation and show that investment in information and communication technology leads to longer job durations. As far as we can tell, there are no works that study the technology-skill complementarity effect on the hazard of job separation and how this hazard changes with tenure.

Farber (1994) establishes that the hazard of job ending, after an initial period, decreases with tenure.³ A possible explanation comes from the accumulation of specific human capital (Becker 1994). During the job relationship, both the company and the worker invest in human capital specific to the firm. These investments increase the worker's productivity in the current company more than in any other company. Because the worker benefits more from the investment in the current company, given her added productivity, she has an incentive to stay. Similarly, the company has an incentive in retaining the worker because to bring another worker to the same level of productivity would again require an investment in training. Thus, as tenure grows, specific human capital is accumulated, and the separation rate goes down (Parsons 1972; Jovanovic 1979a).

Another explanation comes from matching theory (Jovanovic 1979b) in which the quality of the match between worker and employer is seen as an experience good: as tenure increases, both parties learn about the quality of the match. In each period, the bad matches are terminated and all that remains are the good ones. Generally, information about the match quality can also be regarded as a form of specific capital (Farber 1999).

Under the hypothesis of technology-skill complementarity, we can expect specific human capital to be valued more in technology intensive industries. These industries require more skills, and technology will make skilled workers relatively more productive than less-skilled workers.

In the literature, we can find evidence that more technology demands more specific human capital, mostly in the form of on-the-job training (Lillard and Tan 1986; Greenhalgh and Mavrotas 1996; Bartel and Sicherman 1998). Tan (1991) proposes that, because of the novelty of the technology used, the necessary skills cannot be found outside the company and so the best solution for the development of skills is to provide training. Relating technology with the effect of accumulation of specific human capital on turnover, Mincer

³ Also see Farber (1999) for a survey on job duration and how it relates to specific human capital and matching theory.

(1989) finds that, where there is more technological change, workers receive more on-the-job specific training which, in turn, drives smaller turnover. This leads us to expect that the more intense the technology is, the smaller the hazard of job separation will be.

Technological change can, conversely, render previously acquired human capital obsolete. This could mean that in more technology intensive industries, human capital is not as important because it is systematically being replaced. If, however, obsolescence is only partial (which might be a more adequate hypothesis than absolute obsolescence), successive training will result in the accumulation of specific skills through time, even if at a slower rate (Mincer 1989). Additionally, if technological change is carried out by skilled workers (rather than being exogenous), workers will have incentives to develop, implement and use technologies that are complementary to their sets of skills, instead of technologies that erode their skills (Acemoglu 1998).

General human capital, in the form of formal education, also plays a role in determining separation rates. More educated workers have acquired more skills (Becker 1994), or, alternatively, their education functions as a signal of their skills (Spence 1973), and so they will be more productive than less-educated workers. Firms will make additional efforts to retain these more productive workers, meaning smaller turnover. We can think of this difference in separation rates between educated and uneducated workers as an education-premium on separation rates.

Again, because technology and skills are complementary, we expect the education premium to be larger in more technology intense industries.

The relative advantages in the implementation and use of new technology brought by education (Bartel and Lichtenberg 1987) lead to a higher demand for more educated workers in technological sectors. Educated workers will also be worth more in technological firms because they are more likely to receive firm-specific training (Mincer 1988; Bartel and Sicherman 1998) which, as we have seen, is more necessary in those sectors.

The same argument can be extended to other measures of human capital other than education and specific training, such as hierarchical position or

level of responsibility within the firm.

In conclusion, the literature points in the direction that growing technology intensity leads to lower separation rates because of higher human capital requirements in more technological industries and also because of complementarity between technology and skills.

3. Data

We use a longitudinal matched employer-employee data set - *Quadros de Pessoal* containing every private firm in Portugal with at least one paid employee. The data set originates from a mandatory yearly survey submitted to the Portuguese Ministry of Employment and Social Security since 1985. It includes detailed information on workers, firms and establishments and a unique identification number for workers and companies, it allows for the mapping of workers' job-to-job flows. At worker level, the information includes gender, age, skill level, formal education, date of admission in the company. The information for firms includes number of employees, year of foundation and industry. We use data covering the period from 1995 to 2007, which roughly translates to an average of 2.5 million workers per year and 200,000 firms per year.⁴

The extension and detail of the data set allows us to investigate issues that require large samples, while at the same time controlling for numerous heterogeneity factors and following individuals throughout their careers.

Our analysis begins in 1995 because of availability of data and ends in 2007, so as to exclude the effects of the international financial crisis that started in 2008.

We limit the analysis to workers in manufacturing companies that do not close during the studied period as the reasons for closure would dominate the reasons for job separation.⁵

Job separation, in this context, is said to have happened if the worker is

⁴ However, data for workers is missing in 2001.

⁵ In the original data set around 43% of the companies close between 1995 and 2007.

not in the same company in two consecutive years or if the date of admission in the same company is different in two consecutive years. This can happen in three ways: the worker left the data set and is not observed for some period of time; the worker is in a different company in two consecutive years either because she left by her own will or was laid off; the worker left the company for some time and rejoined its ranks later. We treat all of these cases of job separation in the same way and cannot distinguish between voluntary exits and forced exits because the reason of separation is not declared.

The sample is restricted to workers who start a new job relationship in the studied time frame. We follow the worker up to the first occurrence of job separation, thus limiting our analysis to the first observed working spell. If a worker does not experience job separation in the time frame, we say the spell is censored. By only observing new job relationships, instead of ongoing ones, we can correctly identify when the spell starts – and therefore its total duration – and the initial conditions. This avoids the problems that may arise from having left-censored or left-truncated observations. It may, however, lead to selection bias by systematically dismissing observations with longer durations. In practice, we limit job durations to 13 years, but even if selection bias occurs, 82% of all jobs have durations of less than 13 years.

The choice of having only one working spell per worker has two justifications. The first is that some of the tools used do not handle multiple spell data. The second reason is related to only having companies that do not close. Having multiple spells per worker would mean that we could only observe the second working spell if she joined a company that did not close in the 1995-2007 time frame, after leaving a company that also did not close. This would cause selection bias in the subsequent job spells.

Only workers who are at least 16 years old when they start the working spell are considered and workers are censored after their 55th birthday.⁶ Excluding the age of retirement is particularly important because it has been

⁶ In Portugal the official retirement age is 65 years, but some contractual schemes allow entering into a period of pre-retirement starting at the age of 55.

shown that technology affects the retirement decision (Allison 1982).

Companies are classified into three categories of manufacturing technology intensity – High-technology, Medium-technology and Low-technology – according to OECD's⁷ definition of technology intensity based on direct R&D intensity using Eurostat's version with NACE Rev 1.1 codes. The Medium-technology category aggregates both Medium-high and Medium-low-technology categories of OECD's definition for a more parsimonious analysis. Because some companies change their NACE codes during the observed period, we classify the companies according to the code in the first year of observation.

Some gaps exist in the original data. Namely, for some workers the admission date is earlier than the year of the first observation. If the difference is smaller than three years, we rebuild the worker's history up to the admission date assuming most of the data remains unchanged. Other kinds of gaps that exist during the worker's tenure are also fixed. In general, the assumption of unchanged data is not too strong because we are mostly concerned with details about the worker, like education and level of skills, in the moment she joins the company. After applying these restrictions and removing invalid observations or with incomplete information, our final working sample consists of 2,205,820 observations corresponding to 614,335 different subjects with 401,984 job separations in 29,005 firms.

Table 1 shows some descriptive statistics for the main variables used in our analysis, across the three technology categories. Portugal's population is relatively uneducated (79% of the observations hold no more than four years of schooling at the beginning of the job relationship), and there is a much higher concentration of more educated workers in the high-tech manufacturing industries. The proportion of workers with high school education or university education increases with technological intensity: from 12% to 39% for workers with high school and from 5% to 20% for workers with at least college educa-

⁷ <http://www.oecd.org/sti/ind/48350231.pdf> See the Appendix for details on the OECD classification.

tion. One would expect this to happen, given that the more complex the process of manufacturing is the more education is required to execute the process (Doms, Dunne, and Troske 1997; Machin and Van Reenen 1998).

TABLE 1 DESCRIPTIVE STATISTICS

| | High-tech | Medium-tech | Low-tech | Total |
|---------------------------------|--------------------|--------------------|-------------------|--------------------|
| Education at entry | | | | |
| <i>Primary</i> | 0.41 (0.49) | 0.74 (0.44) | 0.84 (0.37) | 0.79 (0.41) |
| <i>High School</i> | 0.39 (0.49) | 0.18 (0.38) | 0.12 (0.32) | 0.15 (0.36) |
| <i>University</i> | 0.2 (0.4) | 0.08 (0.27) | 0.05 (0.21) | 0.06 (0.25) |
| Skill level at entry | | | | |
| <i>Very high skills</i> | 0.17 (0.37) | 0.06 (0.23) | 0.03 (0.18) | 0.05 (0.21) |
| <i>High skills</i> | 0.19 (0.39) | 0.05 (0.22) | 0.05 (0.21) | 0.05 (0.22) |
| <i>Medium skills</i> | 0.25 (0.43) | 0.37 (0.48) | 0.36 (0.48) | 0.36 (0.48) |
| <i>Low skills</i> | 0.18 (0.39) | 0.31 (0.46) | 0.32 (0.47) | 0.31 (0.46) |
| Tenure | 3.58 (2.8) | 3.62 (2.77) | 3.64 (2.74) | 3.63 (2.75) |
| Female | 0.46 (0.5) | 0.27 (0.45) | 0.55 (0.5) | 0.44 (0.5) |
| Age at entry | 27.59 (7.61) | 28.7 (9.04) | 28.84 (9.33) | 28.74 (9.16) |
| Firm size (Number of employees) | 595.98 (650.95) | 380.72 (926.57) | 138.48 (235.1) | 250.56 (637.71) |
| Company age | 23.97 (21.17) | 21.02 (16.66) | 20.31 (18.36) | 20.72 (17.82) |
| Number of observations | 73,196 | 882,370 | 1,250,254 | 2,205,820 |
| Number of workers | 21,238 | 251,881 | 341,216 | 614,335 |
| Number of job separations | 14,804 | 168,376 | 218,804 | 401,984 |
| Proportion of job separations | 69.7% | 66.8% | 64.1% | 65.4% |
| Number of companies | 496 | 10,710 | 17,799 | 29,005 |

Note: This table reports mean values and standard deviations (in parentheses) for our sample. The values are computed considering all observations for each individual. Workers with longer tenures contribute more observations to the calculations.

We use education level at entry in the company, instead of the degree the worker holds in each year, to avoid confusion between the effects of education and the effects of a change on education level on the hazard of job

separation, even though most workers do not change their education once they join the labor market.

The data set contains information on an eight-level multidimensional measure of skills that integrates job level, task complexity, skill requirements for job and degree of responsibility. We summarize that information in a five-level skill variable: very high skills level includes top and intermediate managers; high skills level includes supervisors, team leaders and higher-skilled professionals; medium skills includes skilled professionals; low skills includes semi-skilled and unskilled professionals; no skills level includes trainees and apprenticeships and in many companies functions as a level of entry or a trial level. Because the company defines this variable, we can think of it as a measure for the quality of the employer-employee match and also as a measure of how specific the worker's skills are to the firm.

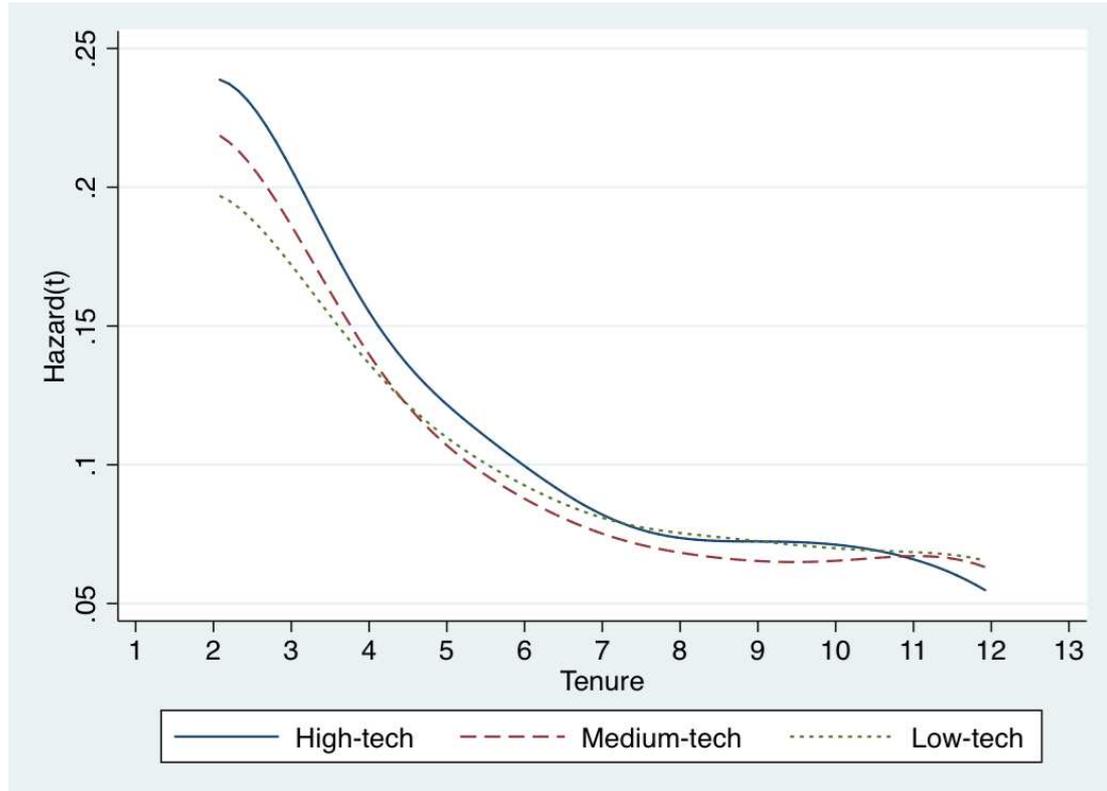
In the sample, the proportion of workers who start their jobs with very high or high skills grows with increasing technological intensity, being much higher in high technology companies than in less technological companies, consistent with Doms, Dunne, and Troske's (1997) findings. As with education, we consider the worker's skill level at the beginning of the job relationship and let the worker's progression within the firm be captured by the shape of the (baseline) hazard. Despite hiring more educated and more skilled workers, tenures are, on average, smaller in high-tech companies even though the difference to less technological companies is small. This is also in line with the proportion of job separations observed in the sample.

The more technological a company is, the younger the workers are, on average, when they start their jobs. In high-tech companies, the average age of entry is smaller by more than a year than in medium technology firms. Considering high-tech workers are also more educated, this reveals that those workers have less labor market experience than their less technological counterparts. Finally, the descriptive statistics show that, on average, company's size and age increases with technology intensity.

Figure 1 represents an estimate of the empirical hazard functions by technology intensity based on the Nelson-Allen estimator for the cumulative

hazard function.⁸ The estimated hazard of job separation decreases with tenure but we cannot say that one level of technology intensity has the highest hazard for every year of tenure. However, in general, workers in high-tech seem to experience higher hazards until their seventh year of tenure and then share the same level of hazard as workers in low-tech companies.

FIGURE 1 NELSON-ALLEN ESTIMATES FOR HAZARD OF JOB SEPARATION BY TECHNOLOGY INTENSITY



Whilst the data is extensive in number of observations and has detailed information for workers and companies, it has some limitations. As *Quadros de Pessoa* provides one observation per worker per year the data is naturally set in the form suggested by Jenkins (1995) for discrete-time models. We cannot identify precisely the moment when job separation occurs. We only know that it happens sometime in a one-year interval. This may lead to over-

⁸ The method used for estimation uses kernel-based smoothing, which averages values in the neighborhood of the estimated point using a Gaussian kernel. In this case, we use a smoothing bandwidth of 1 point before and after the point being estimated. That is why there are no estimates for the first and last years.

estimation or underestimation of tenures. Furthermore, shorter-term job relationships that start and end between annual observations are not present in the sample.

The definition of technology intensity may also be problematic. Because it is a relative measure, classifying a company as medium-tech only means that it is relatively less technologically intense than other high-tech companies even though it may actually be considered as a high technology by some other perspective. Furthermore, this definition does not consider technology at the product level. A low-tech company may produce technology intensive products.

Because we do not have information about the tasks performed by a worker, we assume that technology intensity relates to every worker in the company in the same way. This may not always be true, as we would expect that, for example, an accounting job in a high-tech company is not much different than one in a low-tech firm.

The sample also contains relatively few high-tech companies (about 1.7% of the observations) and so the observed behaviors may be associated with those specific companies rather than the level of technology. However, the proportion of high-tech companies in the sample follows that of the original data set (around 1.3% of the observations are high-tech). Portugal is mostly a services economy and low-tech companies dominate its manufacturing industries.

4. Model

To understand how the relationship between skills and the hazard of job separation and how it changes with technological intensity, we used discrete-time proportional hazards models with unobserved heterogeneity (Lancaster 1979; Nickell 1979). The hazard of job separation at moment t , in this context, is the probability of a worker experiencing a job separation at that moment, conditional upon having had a tenure of t periods.

We applied three different specifications to each of the three technological intensity categories. The proportional hazards model has the following form:

$$\lambda_i(t) = \theta_i \lambda_0(t) \exp(z_i(t)' \beta) \quad (1)$$

where λ_i is the hazard of job separation for worker i with tenure t , θ_i is the unobserved heterogeneity random variable for that worker, $\lambda_0(t)$ is the baseline hazard function of tenure, $z_i(t)$ is the vector of explanatory variables for worker i and β is the vector of parameters to be estimated. The expression can be rewritten to take the form of a complementary log-log model that can be estimated with maximum likelihood.

The baseline hazard function is a function of tenure. It represents how the hazard varies with tenure if all the other explanatory variables are at their base levels. These models are said to be proportional because they assume that the ratio between the baseline hazard and an individual's hazard is the same in any moment in time (Allison 1982).

Even though economic theory gives us no justification for the proportional hazards assumption, the proportional hazards model is popular in the labor economics literature because, in general, better alternatives do not exist (van den Berg 2001). The availability of a wide range of tools also justifies the usage of this model. Furthermore, even when we cannot assume proportionality, the model is thought to be a good enough approximation (Allison 1984).

We do not know the exact moment job separation occurs. Because our data are yearly, we only know that job separation happens some time during the year interval. Workers who experience job separation in the same year but in different months are observed to leave their jobs in the same moment – there is a tie in the job separation moment. This causes interval-censoring and leads to wrong estimates. This problem is especially relevant when the unit of time is a large fraction of the mean duration (Jenkins 2005). In our case, one year represents around one third of the mean tenure. To avoid these problems, we used a discrete-time formulation (Allison 1982) that handles

both interval-censoring and tied survival times. In particular, our choice is the discrete-time proportional hazards model proposed by Prentice and Gloeckler (1978) that follows a complementary log-log specification. In this case, the discrete time hazard function is given by:

$$\lambda_i(t) = 1 - \exp[-\exp(z_i(t)' \beta + c(t))] \quad (2)$$

Where $c(t)$ is a function of tenure that relates to the baseline hazard in the t^{th} year of tenure.

The misspecification of the baseline hazard, when using single-spell data, causes incorrect parameter estimates (van den Berg 2001). The literature gives no indication on the functional form of the baseline hazard function of job separation. Our choice was a flexible specification using a piecewise constant function (Meyer 1990), where we assume the hazard rate is constant within each year, but can be different for every year. By allowing the baseline to take any shape, we can obtain consistent estimates of the parameters. For this purpose, we created thirteen dummy variables corresponding to each possible year of tenure.

Parameter estimates are also sensitive to misspecification of the distribution for unobserved heterogeneity (van den Berg 2001). Farber (1999) suggests that, in the particular case of job duration models, unobserved heterogeneity plays an important role in the estimates. Unobserved heterogeneity may originate from omitted variables or from measurement errors in observed survival times or regressors. It can lead to a bias of the regression coefficients that can be even more serious than the bias present in ordinary regression (Nickell 1979) and may give us over-estimated coefficients for negative duration dependence (Lancaster 1990).

There are different solutions to handle unobserved heterogeneity issues in discrete-time duration models (Lancaster 1990). A popular parametric approach is modeling it using a Gamma distribution with mean one and variance σ^2 (Meyer 1990). This distribution has a closed form expression for the hazard function and so can be estimated directly with maximum likelihood. Another

parametric alternative assumes that the unobserved heterogeneity follows a Normal distribution. The hazard function has no closed form expression requiring computationally intensive numerical methods like quadrature integration to estimate the distribution's parameter. Heckman and Singer (1984) propose an approach which eschews any parametric assumptions about the form of the distribution and instead fits an arbitrary distribution where each worker has a probability of belonging to a certain region of the distribution (mass points).

The main choice for our models, because of its tractability and ease of estimation, was the Gamma specification. In that regard, Abbring and van den Berg (2007) found that the distribution of the heterogeneity among survivors converges to a Gamma distribution in a large number of cases, making it a preferred choice for many researchers. For robustness sake, we also ran models with the Normal distribution and with the Heckman and Singer approach.

Nicoletti and Rondinelli (2010) suggest that misspecifying the unobserved heterogeneity does not bias covariate coefficients much but one should pay special attention to the bias of the baseline hazard function. We mitigate the bias by choosing a flexible baseline hazard function (Dolton and van der Klaauw 1995).

We estimate each technology intensity category separately, allowing for a more parsimonious approach rather than interacting explanatory variables with dummy variables for each category. It would be too restrictive to impose the same parameters across the three technology categories. By treating each category separately we also allow the unobserved heterogeneity distributions to have different variances for each technology category. If high skilled workers self-select into companies that use more technology, having a dedicated distribution for those workers may reduce the bias while at the same time allowing for a fairer comparison between technology categories.

We specify dummy variables for worker education level at the start of the job relationship: tertiary education (*University*), secondary education (*high school*) and primary education – the base case. We expect that the higher the

level of education is, the smaller the hazard will be within each category of technology. Across the categories, education should exhibit complementarity with technology intensity, being larger the more technological intense the category is. For example, the effect of having a university degree (compared to the baseline) should be larger for workers in high-tech companies than workers in medium-tech companies.

To further ascertain the effects of skills on the hazard of separation, another specification included dummy variables for levels of the multidimensional variable of skills: very high skills, high skills, medium skills and low skills as the point of comparison. These dummy variables represent the initial level of skills the worker had when she joined the company, from the company's perspective. We anticipate that, within each category of technology, the higher the degree of skills is, the smaller the hazard will be. Across levels of technology, we expect the effects of skills to be larger the more intense the use of technology is because of technology-skill complementarity.

We analyze education and skills in separate specifications because of the correlation between the variables – workers with more education will also occupy higher positions inside the company and have more skills. Treating the variables independently offers a clearer estimate of the effects.

However, we also use a third specification that includes both the education at entry and the level of skills at entry. A more complete specification provides a more accurate estimate of the baseline hazard and reveals how the education and skills variables work together. With this specification, we expect to see workers in more technologically intense environments have a lower baseline hazard, because of the higher requirements in specific human capital.

Besides our variables of study, all models include controls for other worker characteristics, company characteristics and macroeconomic variables.

On the worker side, we control for gender, age at entry and its square, a dummy variable that indicates if she is working part-time (working less than 140 hours per month) and dummy variables for cohorts at entry. For the firm,

we have controls for different types of legal structure, a dummy variable to identify firms with some foreign-owned equity, the logarithm of the number of employees, the logarithm of the company's age when the worker joined, region and industry. To capture macroeconomic trends we include controls for contemporaneous Gross Domestic Product growth rate and contemporaneous unemployment rate. In general our models have the advantage of being parsimonious and give a direct estimation of the baseline hazard function, while at the same providing a clear interpretation for the effects of education and other skills.

5. Results

We estimate our three hazard models with maximum likelihood for each of the three technology categories. The first model is intended to capture the effect on the hazard of separation of the level of education at the beginning of the labor relationship. The second model reveals the effects of an aggregate measure of skills at entry. Finally, the third model includes both education and skills at entry and is designed to provide a more accurate estimate of how the hazard varies with tenure and also how the effects of education change once we account for other skills.

The following tables with estimation results display hazard ratios instead of the regression coefficients. We obtain hazard ratios by exponentiating the regression coefficients. They indicate how the hazard changes compared to the baseline hazard when the corresponding covariate varies by one unit. Hazard ratios allow for an easier interpretation of the effects in relation to the baseline hazard function. For example, a hazard ratio of 0.90 for tertiary education would mean that a worker with a college degree has, on average, a hazard that is 90% of the baseline hazard.

Table 2 presents the estimations results for the education at entry specification. In all technology categories, the hazard ratios for secondary or tertiary education at entry are smaller than one. Workers who start their jobs with more than just primary education have smaller hazards of job separation than the base group. Furthermore, comparing the hazard ratios for secondary and

tertiary education reveals that the effect of education increases with level of education. The difference between the hazard ratios of secondary and tertiary education, weighted across all technology categories, is around 13 percentage points. Also, the difference of the coefficients for each education level is statistically significant, within all technology categories. These results suggest that the more formal education a worker has the smaller the likelihood of job separation will be.

Across the manufacturing categories, we can infer that higher education is complementary with technology. The proportional effects of tertiary education on hazard of job separation are larger the more technologically intense the manufacturing is. In high-tech industries, a worker holding a university degree experiences, on average, a hazard of separation that is around 66% of the hazard for workers with basic education, whereas the hazard for workers with tertiary education is 75% of the baseline hazard in medium-tech companies and 84% in low-tech companies.

Regarding secondary education, however, the proportional effect is less intense in high-tech than it is in medium-tech. The difference is small (hazard ratios are 0.898 for high-tech and 0.862 for medium-tech) and might be explained by a greater need of more educated workers in more technological companies. In such companies, workers with only a high school diploma may be limited to less essential functions and are more easily replaceable. Even if those workers perform complex tasks, they might face a risk of being substituted by a worker with a university degree that will perform better. An alternative explanation is that perhaps there is some sort of a glass ceiling for less educated workers.

The hazard ratios for tenure indicate that the baseline hazard function is smaller in the more technological categories. We should note, however, that the hazard ratios for tenure are not the baseline hazard function but do give an adequate approximation to it.

TABLE 2 HAZARD OF JOB SEPARATION: EDUCATION AT ENTRY SPECIFICATION

| | High-tech | Medium-tech | Low-tech |
|--|---------------------|---------------------|---------------------|
| Secondary Education | 0.898*** (0.021) | 0.862*** (0.006) | 0.972*** (0.008) |
| Tertiary Education | 0.663*** (0.023) | 0.749*** (0.009) | 0.839*** (0.011) |
| tenure = 1 | 0.011*** (0.002) | 0.133*** (0.006) | 0.165*** (0.009) |
| tenure = 2 | 0.013*** (0.002) | 0.104*** (0.005) | 0.145*** (0.008) |
| tenure = 3 | 0.011*** (0.002) | 0.095*** (0.005) | 0.146*** (0.009) |
| tenure = 4 | 0.007*** (0.001) | 0.057*** (0.003) | 0.108*** (0.006) |
| tenure = 5 | 0.007*** (0.001) | 0.049*** (0.003) | 0.096*** (0.006) |
| tenure = 6 | 0.006*** (0.001) | 0.041*** (0.002) | 0.089*** (0.006) |
| tenure = 7 | 0.004*** (0.001) | 0.033*** (0.002) | 0.071*** (0.005) |
| tenure = 8 | 0.004*** (0.001) | 0.032*** (0.002) | 0.074*** (0.005) |
| tenure = 9 | 0.005*** (0.001) | 0.030*** (0.002) | 0.073*** (0.005) |
| tenure = 10 | 0.005*** (0.001) | 0.029*** (0.002) | 0.067*** (0.005) |
| tenure = 11 | 0.005*** (0.001) | 0.033*** (0.002) | 0.071*** (0.005) |
| tenure = 12 | 0.004*** (0.001) | 0.033*** (0.002) | 0.070*** (0.005) |
| tenure = 13 | 0.002*** (0.001) | 0.023*** (0.002) | 0.071*** (0.006) |
| Gamma Variance (σ^2) | 0.302*** (0.095) | 0.139*** (0.024) | 0.492*** (0.024) |
| Number of observations | 73,196 | 882,370 | 1,250,254 |
| Number of workers | 21,238 | 251,881 | 341,216 |
| Log likelihood | -33,752.2 | -396,391.8 | -538,259.4 |
| Log likelihood for model with no unobs. heterog. | -33,758.8 | -396,410.1 | -538,563.5 |
| p-value for LR test of $\sigma^2=0$ | 0.000 | 0.000 | 0.000 |

Notes: This table reports the hazard ratios and standard errors (in parentheses) for maximum likelihood estimation of hazard of job separation on level of education.

Values for tenure variables represent the baseline hazard function.

The model is a cloglog with unobserved heterogeneity following a Gamma distribution.

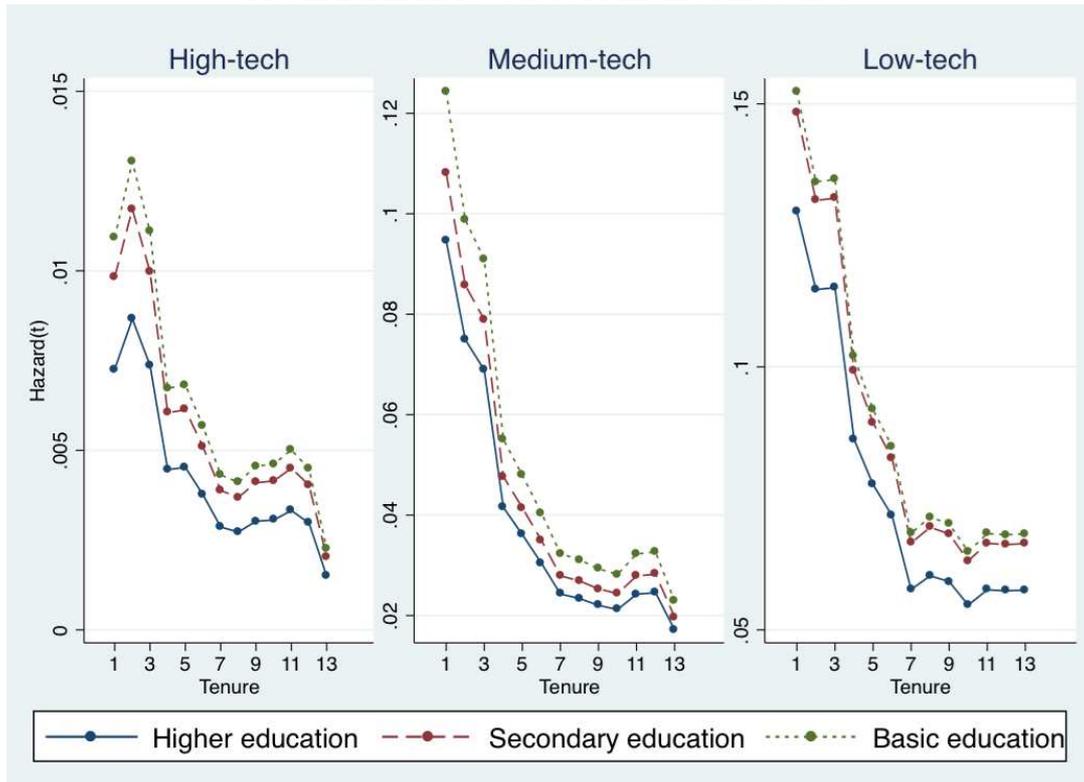
Regressions include controls for gender, worker's age at entry and its square, dummy for part time workers, cohort, firm's type of legal structure, presence of foreign-owned equity, log of number employees, log company's age at entry of worker, region, industry, GDP growth rate and unemployment rate.

Base case is a worker with primary education.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Figure 2 represents the hazard functions for the three levels of education in each technology intensity category. As expected, the hazard of job separation decreases with tenure and it is clear how large the effect of holding a university diploma is, relative to the base case. It is important to say that, even though the proportional effects of education are larger in high-tech industries, the absolute effect might not be. In fact, because the baseline hazard for high-tech workers is much smaller than in other industries, the absolute effect of education is also small.

FIGURE 2 HAZARD FUNCTIONS BY LEVEL OF EDUCATION



The results obtained from the education at entry specification confirm that the more education a worker has at the moment of entry in the company, the smaller the hazard of job separation will be and this effect is proportionately greater the more technologically intense the manufacturing is.

The results of the skills specification are presented in Table 3. In general, higher skills at entry decrease the hazard ratio, that is to say the proportional effect of skills increases with skill level.

However, this is not true for workers with high skills and medium skills in high-tech companies. The hazard ratio of medium skills at entry is 69,6% whereas for high skills the ratio is 73,3%. This may be associated with the definition of the skills variable. The high skills level, besides including higher-skilled professionals as declared by the company, also includes supervisors and team leaders while the medium skills level includes workers that the company considers to be skilled. In some high-tech companies, for example, supervisors of manufacturing in a factory may not be more skilled than a medium-level engineer, even though the supervisors occupy a higher position in the hierarchy.

TABLE 3 HAZARD OF JOB SEPARATION: SKILLS AT ENTRY SPECIFICATION

| | High-tech | Medium-tech | Low-tech |
|--|---------------------|---------------------|---------------------|
| Very High Skills | 0.503*** (0.022) | 0.622*** (0.010) | 0.657*** (0.011) |
| High Skills | 0.733*** (0.026) | 0.735*** (0.011) | 0.738*** (0.011) |
| Medium Skills | 0.696*** (0.023) | 0.852*** (0.007) | 0.864*** (0.006) |
| tenure = 1 | 0.014*** (0.003) | 0.126*** (0.006) | 0.154*** (0.009) |
| tenure = 2 | 0.017*** (0.003) | 0.103*** (0.005) | 0.138*** (0.008) |
| tenure = 3 | 0.015*** (0.003) | 0.097*** (0.005) | 0.141*** (0.008) |
| tenure = 4 | 0.009*** (0.002) | 0.059*** (0.003) | 0.105*** (0.006) |
| tenure = 5 | 0.009*** (0.002) | 0.052*** (0.003) | 0.095*** (0.006) |
| tenure = 6 | 0.008*** (0.001) | 0.044*** (0.003) | 0.088*** (0.006) |
| tenure = 7 | 0.006*** (0.001) | 0.035*** (0.002) | 0.071*** (0.005) |
| tenure = 8 | 0.006*** (0.001) | 0.034*** (0.002) | 0.074*** (0.005) |
| tenure = 9 | 0.006*** (0.001) | 0.033*** (0.002) | 0.073*** (0.005) |
| tenure = 10 | 0.006*** (0.001) | 0.032*** (0.002) | 0.068*** (0.005) |
| tenure = 11 | 0.007*** (0.001) | 0.036*** (0.003) | 0.072*** (0.005) |
| tenure = 12 | 0.006*** (0.001) | 0.037*** (0.003) | 0.072*** (0.006) |
| tenure = 13 | 0.003*** (0.001) | 0.026*** (0.003) | 0.073*** (0.007) |
| Gamma Variance (σ^2) | 0.325*** (0.090) | 0.253*** (0.027) | 0.559*** (0.024) |
| Number of observations | 73,196 | 882,370 | 1,250,254 |
| Number of workers | 21,238 | 251,881 | 341,216 |
| Log likelihood | -33,641.8 | -395,998.6 | -537,712.3 |
| Log likelihood for model with no unobs. heterog. | -33,650.7 | -396,051.6 | -538,094.8 |
| p-value for LR test of $\sigma^2 = 0$ | 0.000 | 0.000 | 0.000 |

Notes: This table reports the hazard ratios and standard errors (in parentheses) for maximum likelihood estimation of hazard of job separation on level of skills.

Values for tenure variables represent the baseline hazard function.

The model is a cloglog with unobserved heterogeneity following a Gamma distribution.

Regressions include controls for gender, worker's age at entry and its square, dummy for part time workers, dummy for workers with no skills, cohort, firm's type of legal structure, presence of foreign-owned equity, log of number employees, log company's age at entry of worker, region, industry, GDP growth rate and unemployment rate.

Base case is a worker with low skills.

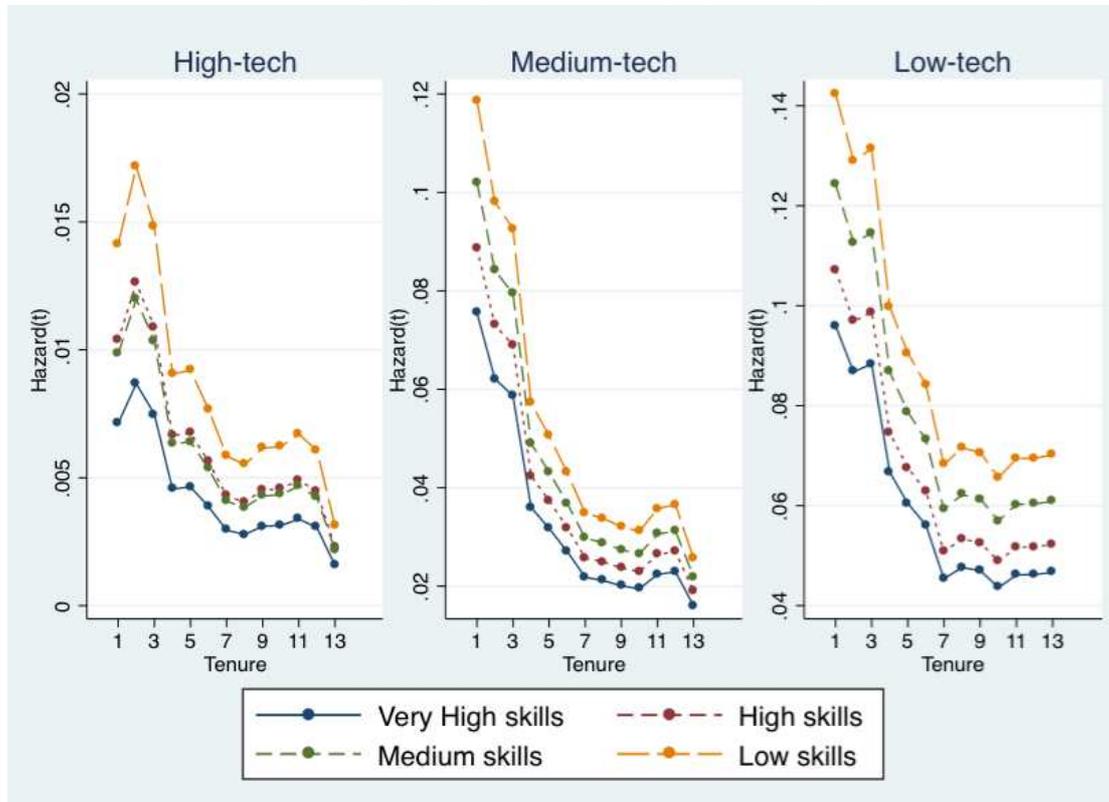
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

For every level of skills at entry, the proportional effects are greater the more technologically intense the industry is, again exhibiting technology-skill complementarity.

As with the education specification, the hazard ratios for the tenure variables suggest that the baseline hazard is smaller the more technological the industry is. In Figure 3 the hazard functions are plotted for every level of skills

at entry in the three categories of technology. It becomes clear that, in general, the higher the level of skills the lower the hazard function will be.

FIGURE 3 HAZARD FUNCTIONS BY LEVEL OF SKILLS



The findings from the skill at entry specification confirm that the more skills a worker has at the moment of entry in the company, the smaller the hazard of job separation will be and this effect is proportionately greater the more technologically intense the sector is.

The results for our complete specification, that includes both education at entry and skills at entry, are shown in Table 4. This specification provides a more accurate estimate of the baseline hazard functions of tenure and also makes it possible to analyze the effects of skills at entry when we control for education and vice-versa. The hazard ratios for the tenure dummy variables in high-tech are smaller than in medium-tech and, in turn, these hazard ratios for medium-tech are smaller than for low-tech. The hazard ratios for tenure in high-tech are around 5 to 10 times smaller than those in medium-tech. This indicates that the baseline hazard function for high-tech workers is much low-

er than workers in any of the other technology categories.

TABLE 4 HAZARD OF JOB SEPARATION: COMPLETE SPECIFICATION

| | High-tech | Medium-tech | Low-tech |
|--|---------------------|---------------------|---------------------|
| Secondary Education | 0.952** (0.023) | 0.889*** (0.007) | 1.016* (0.009) |
| Tertiary Education | 0.889*** (0.034) | 0.946*** (0.014) | 1.041** (0.017) |
| Very High Skills | 0.545*** (0.028) | 0.646*** (0.012) | 0.641*** (0.013) |
| High Skills | 0.759*** (0.028) | 0.760*** (0.012) | 0.729*** (0.011) |
| Medium Skills | 0.706*** (0.023) | 0.863*** (0.007) | 0.862*** (0.006) |
| tenure = 1 | 0.014*** (0.003) | 0.127*** (0.006) | 0.154*** (0.009) |
| tenure = 2 | 0.017*** (0.003) | 0.104*** (0.005) | 0.138*** (0.008) |
| tenure = 3 | 0.014*** (0.003) | 0.098*** (0.005) | 0.141*** (0.008) |
| tenure = 4 | 0.009*** (0.002) | 0.059*** (0.003) | 0.105*** (0.006) |
| tenure = 5 | 0.009*** (0.002) | 0.052*** (0.003) | 0.095*** (0.006) |
| tenure = 6 | 0.007*** (0.001) | 0.044*** (0.003) | 0.088*** (0.006) |
| tenure = 7 | 0.006*** (0.001) | 0.035*** (0.002) | 0.071*** (0.005) |
| tenure = 8 | 0.005*** (0.001) | 0.034*** (0.002) | 0.074*** (0.005) |
| tenure = 9 | 0.006*** (0.001) | 0.033*** (0.002) | 0.073*** (0.005) |
| tenure = 10 | 0.006*** (0.001) | 0.032*** (0.002) | 0.068*** (0.005) |
| tenure = 11 | 0.006*** (0.001) | 0.036*** (0.003) | 0.072*** (0.005) |
| tenure = 12 | 0.006*** (0.001) | 0.037*** (0.003) | 0.072*** (0.006) |
| tenure = 13 | 0.003*** (0.001) | 0.026*** (0.003) | 0.073*** (0.007) |
| Gamma Variance (σ^2) | 0.327*** (0.090) | 0.248*** (0.027) | 0.559*** (0.024) |
| Number of observations | 73,196 | 882,370 | 1,250,254 |
| Number of workers | 21,238 | 251,881 | 341,216 |
| Log likelihood | -33,636.7 | -395,881.4 | -537,708.3 |
| Log likelihood for model with no unobs. heterog. | -33,645.7 | -395,933.3 | -538,089.7 |
| p-value for LR test of $\sigma^2=0$ | 0.000 | 0.000 | 0.000 |

Notes: This table reports the hazard ratios and standard errors (in parentheses) for maximum likelihood estimation of hazard of job separation on level of education and level of skills.

Values for tenure variables represent the baseline hazard function.

The model is a cloglog with unobserved heterogeneity following a Gamma distribution.

Regressions include controls for gender, worker's age at entry and its square, dummy for part time workers, dummy for workers with no skills, cohort, firm's type of legal structure, presence of foreign-owned equity, log of number employees, log company's age at entry of worker, region, industry, GDP growth rate and unemployment rate.

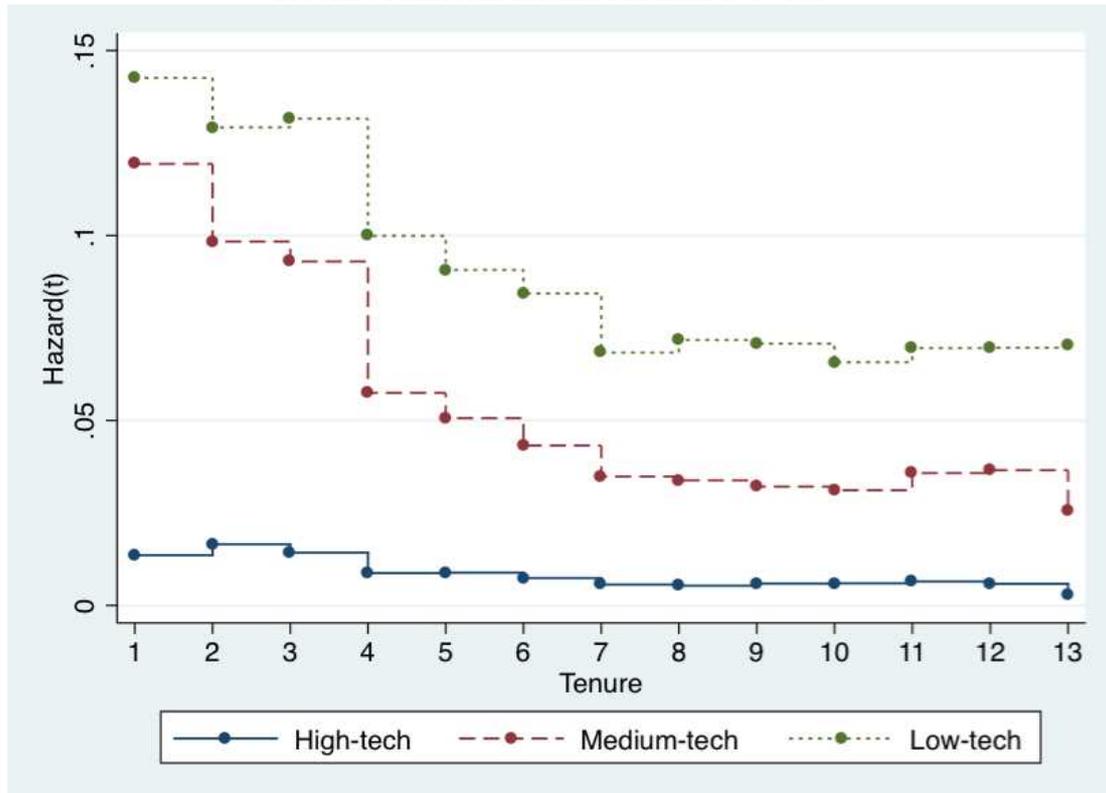
Base case is a worker with primary education and low skills.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Figure 4 represents the baseline hazard functions for each of the three technology intensity categories. The baseline hazard function of tenure is determined using Equation 2 when all other explanatory variables are at their

base level. As expected, in all technology categories, the hazard of job separation decreases as tenure increases. This may be explained by either an accumulation of specific human capital or an increase in the employer-employee match quality, as both the worker and the firm learn more about how well they fit together.

FIGURE 4 PREDICTED BASELINE HAZARD FUNCTIONS



The hazard of job separation for high-tech workers is always under 2% and the difference in baseline hazard between the three technology categories is clear. This difference may suggest a stronger presence of firm-specific human capital as technology intensity grows, or, in other words, representative of a complementarity between technology and specific human capital. Assuming more technological manufacturing requires, in general, more complex tasks and skills that are harder to acquire, once a firm finds a worker capable of performing those tasks it has a stronger incentive to retain the worker. On the other hand, the worker may also realize that her abilities are specific to those tasks or to that firm, which will also provide a greater incentive for her to stay in the firm.

However, we would also expect to see stronger effects of specific human capital accumulation as technology intensity increases. If technological firms' needs of human capital are more specific, each year of tenure would have a larger effect on the hazard, compared to the tenure effect in less technological companies. The slope of the baseline hazard function should be more negative as technology intensity increases. That is not what we observe in our work – the slope of baseline hazard function is much smaller in the high-tech case than in the medium or low-tech category. Mincer (1989) provides a possible explanation for what we observe in the high technology industries: more technological change may render obsolete most of the previously acquired specific human capital and thus there is little accumulation with previous human capital.

There may exist some self-selection of the more able workers to the more technologically intense companies, as suggested by Bartel and Sicherman (1999). Because more able workers experience lower probabilities of job separation, if these workers are sorted into more technological companies, hazards in technology intense industries would be lower. However, if sorting occurred, it is reasonable to expect that the skill-premium would not be larger in industries with more technological change. If workers with more ability were sorted into technology intense companies, the hazard ratios for education and, especially, for the measure of skills should not be larger than those observed in less technological companies because all workers would be amongst the most able. The baseline hazard, itself, would represent the hazard of high ability workers and so there should be almost no proportional effect.

The effects of education at entry decrease when we also include skills at entry in the specification. For example, the hazard ratio for high-tech workers with a university diploma is around 66% in the education specification and becomes 89% in the complete education.

There is also a decline in the effect of skills at entry, but it is much smaller than the reduction in the effect of education. This suggests that, in determining the hazard of job separation, human capital in the form of formal edu-

cation is less relevant than more firm-specific skills.

For every specification, we compared the models with and without Gamma distributed unobserved heterogeneity. In every case, the likelihood-ratio tests indicate that the difference between the models is statistically significant with p-values smaller than 0.1%.

For robustness sake, we also ran models with the Normal distribution and with the Heckman and Singer approach. Using the Normal distribution the results were similar to the Gamma case. However, we found that Heckman and Singer's method was unstable with our data set and could not get definitive results for all of our specifications in each category of technology intensity.

The results suggest that general human capital in the form of education influences the hazard of job separation and is more important in more technological settings: the more educated a worker is, the smaller the hazard of job separation is and the education effect becomes stronger as technology intensity increases.

The results also suggest specific human capital plays a stronger role than general human capital in determining the hazard of job separation and its value is higher in more technological industries. The influence of specific human capital is seen in two ways: the more specific skills a worker has, the smaller the hazard is and the baseline hazard for every year of tenure decreases as technology intensity increases. However, there is no evidence indicating that specific human capital accumulated through tenure is more valuable in high-tech companies than elsewhere.

6. Conclusions

Our analysis suggests technology-skill complementarity is also observable in terms of hazard of job separation. We found that workers experience a lower level of hazard of job separation in every year of their tenure at the company in more technology intensive manufacturing. We also found that there is a reward for starting a job with more education and that the reward for having a tertiary education degree is larger in high-technology industries. Fur-

thermore, by using a multidimensional measure of firm specific skills that include hierarchical level, task complexity, skill requirements for job and degree of responsibility we find that high-skill workers also experience lower levels of hazard of job separation and this premium expands in more technological sectors of manufacture.

Our results could mean that firm-specific human capital is more valued in high-tech firms, possibly because the more complex the technology becomes, the harder it is to acquire technology-specific skills. General human capital also seems to be more highly regarded by those firms, as suggested by the results obtained for education at the beginning of a job relationship. It is likely that firms that need more specific human capital will hire more educated workers in order to hasten the acquisition of those specific skills.

The conclusions above are, however, subject to some limitations. We assume that the distribution of workers among the categories of manufacturing is similar. However, we cannot eliminate the existence of a sorting process whereby the more able workers choose to work in industries where the hazard of job separation is, by itself, lower. Nonetheless, our analysis is focused on effects relative to the base case (for example, looking at the advantage workers with higher education have relative to workers with a basic level of education) meaning that, if there is indeed sorting of skilled workers into more technological sectors, the absolute effects may be even larger.

Also, exits are all treated equally, despite that leaving for a better job is different than leaving to unemployment. According to the way we defined exits, the last kind of exits is much more predominant and our results should not be too affected by this issue.

The analysis presented in this work can be expanded by using other measures of technology intensity, such as R&D expenditure at the firm-level rather than sector-level aggregate measures allowing us to further understand the effects of technology on job separation. In addition, similar analysis should be extended beyond manufacturing industries, by looking at workers in the services sectors.

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Appendix

TABLE A.1 AGGREGATIONS OF MANUFACTURING BASED ON NACE REV. 1.1

| Manufacturing industries | NACE Rev. 1.1 codes | Description |
|--------------------------|---------------------|---|
| High-technology | 24.4 | Manufacture of pharmaceuticals, medicinal chemicals and botanical products |
| | 30 | Manufacture of office machinery and computers |
| | 32 | Manufacture of radio, television and communication equipment and apparatus |
| | 33 | Manufacture of medical, precision and optical instruments, watches and clocks |
| | 35.3 | Manufacture of aircraft and spacecraft |
| Medium-high-technology | 24 | Manufacture of chemicals and chemical product, excluding 24.4 Manufacture of pharmaceuticals, medicinal chemicals and botanical products |
| | 29 | Manufacture of machinery and equipment n.e.c. |
| | 31 | Manufacture of electrical machinery and apparatus n.e.c. |
| | 34 | Manufacture of motor vehicles, trailers and semi-trailers |
| | 35 | Manufacture of other transport equipment, excluding 35.1 Building and repairing of ships and boats and excluding 35.3 Manufacture of aircraft and spacecraft |
| Medium-low-technology | 23 | Manufacture of coke, refined petroleum products and nuclear fuel |
| | 25 to 28 | Manufacture of rubber and plastic products; basic metals and fabricated metal products; other non-metallic mineral products |
| | 35.1 | Building and repairing of ships and boats |
| Low-technology | 15 to 22 | Manufacture of food products, beverages and tobacco; textiles and textile products; leather and leather products; wood and wood products; pulp, paper and paper products, publishing and printing |
| | 36 to 37 | Manufacturing n.e.c. |