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The Struggle of Small Firms to Retain High-Skill Workers:

Job Duration and the Importance of Knowledge Intensity

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In the knowledge economy, skilled workers play an important role in innovation and economic growth. However, small firms may not be able to keep these workers. We study how the knowledge-skill complementarity relates to job duration in small and large firms, using a Portuguese linked employer-employee data set. We select workers displaced by firm closure and estimate a discrete-time hazard model with unobserved heterogeneity on the subsequent job relationship. To account for the initial sorting of displaced workers to firms, we introduce weights in the model according to the individual propensity of employment in a small firm. Our results show a lower premium on skills in terms of job duration for small firms. Furthermore, we find evidence of a strong knowledge-skill complementarity in large firms, where the accumulation of firm-specific human capital also plays a more important role in determining the hazard of job separation. For small firms, the complementarity does not translate into longer job duration, even for those with pay policies above the market. Overall, small knowledge-intensive firms struggle to retain high skill workers and find it harder to leverage the knowledge-skill complementarity.

Keywords: knowledge intensity, technology, firm size, small firms, job duration, skills

JEL codes: J24, J63, M51, O33

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1. Introduction

Technological and economic development in the knowledge economy is predominantly skill-biased, leveraging the complementarity between knowledge investments and skills (Griliches 1969), favoring those better able to create and manipulate knowledge. Skills are increasingly becoming the paramount condition to access high-paying, long-lasting jobs in knowledge-intensive firms, leaving less-skilled workers trapped in low-wage, high-turnover jobs, with fewer ladders for career advancement. This segmentation issue further compounds when one acknowledges that most knowledge-intensive jobs are concentrated in large employers, which adopt more recent technologies (Dunne 1994) and are more capital-intensive (Troske 1999). Furthermore, it is widely accepted that large firms pay higher wages and in general hire more high-skilled workers (Oi and Idson 1999). The same two facts are also verified in more technological firms (Dunne and Schmitz Jr. 1995), thus highlighting that skills are more valued in large technological companies if the technology-skill complementarity hypothesis holds.

The literature has on many occasions explored the relationship between technological change and employment, mostly in the context of manufacturing. In knowledge-based economies, where services are increasingly more predominant, it is more appropriate to think of the progress of knowledge rather than the progress of technology to amplify the scope beyond manufacturing. Throughout the paper, the term knowledge-intensity encompasses both knowledge and technological intensity. All arguments grounded on a narrower definition of technological change still hold in the knowledge-based economy where, as before, workers are required to improve and adapt their skills to cope with innovative progress and increased demand for skills.

Tenures are longer in innovative companies (Mincer 1989) and more technological firms (Castro Silva and Lima 2017), as well as in large organizations (Idson 1996). The more-demanding skill requirements in those businesses call for a more stable workforce that translates into lower separation rates. This may present a challenge to small technology- and knowledge-based firms if they struggle to retain the skilled workforce required for survival and growth. The link between knowledge-skill complementarities and firm size has not been covered in previous works, and it remains to be assessed whether the small-size penalty in separation rates can be compensated by a knowledge premium. In this work, we analyze the relationship between knowledge intensity and job duration, and how this relationship differs in small and large firms. We provide evidence of contrasting skill requirements in small and large companies with distinct levels of knowledge intensity, and how job separation rates vary across the different categories.

We apply discrete-time proportional hazards models with unobserved heterogeneity for several worker skill measures and human capital accumulation, interacted with firm-size categories and knowledge-intensity of the industry to ascertain how knowledge-skill complementarities are influenced by firm size. We use the detailed linked employer-employee data set *Quadros de Pessoal* that originates from a mandatory survey collected by the Portuguese Ministry of Employment. Our identification strategy relies on choosing to study workers displaced by firm closure that then find a job in a new firm (Neal 1995). Goos, Rademakers, and Röttger (2021) suggest that firm closure leads to involuntary separations and could allow for better identification of effects than using job-to-job moves, because it may lessen selection effects that could arise from voluntary firm switches based on unobserved factors. In addition, given that there is evidence of skilled workers sorting into larger companies (Idson and Feaster 1990), our duration models are weighted by the predicted probabilities obtained from a likelihood model of finding a job in a small firm. The weights allow us to control for this possible non-random selection to some extent (Solon, Haider, and Wooldridge 2015).

We find that skilled workers suffer a penalty in terms of job separation hazard if they are employed in small knowledge-intensive firms, showing that these firms might not be able to retain skilled workers. In less knowledge-intensive firms we observe similar levels of a skill premium between small and large firms. Concerning the impact of the accumulation of firm-specific human capital on the hazard of job separation, the pattern is similar for both levels of knowledge intensity in small firms, whereas in larger firms the accumulation of specific human capital is faster and stronger for workers in knowledge-intensive industries. We also consider the influence of the firms' pay policies towards more-able workers and find again that knowledge-intensive small firms cannot guarantee a lower hazard of job separation even when paying above the market wages.

Our results point toward a skill gap between small and large knowledge-intensive firms, which could lead to ever-expanding large firms and dwindling small firms who cannot maintain or grow their ranks of skilled workers necessary for greater innovation, technology adoption and knowledge production.

2. Literature review

2.1. Knowledge intensity, employment and job duration

There is substantial research on the relationship between employment and technological progress.[1] Innovation can lead to an increase in employment levels through product innovation and new business possibilities. The labor-saving nature of process innovation can also result in

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[1] For extensive reviews of technological change's impact on employment, see Vivarelli (2014), Calvino and Virgillito (2018) and Barbieri et al. (2020).

technological displacement and lower levels of employment, although this negative impact might be lessened by indirect price, investment and income compensation mechanisms (Vivarelli 2015). Though there is no consensus on the overall impact, most works suggest that innovation brings net employment growth at the firm level.[2] At higher levels of aggregation, the direction and magnitude of the effect can vary (Calvino and Virgilito 2018). Dosi et al. (2021) show how using industry as the unit of analysis along with the kind of technological change —R&D and product innovation versus (replacement or expansionary) investment and process innovation— can challenge the frequently expected result of net job creation. Employment dynamics will also be determined by the specificities of each economy, namely its distance from the knowledge frontier, the functioning of the labor market and market competitiveness. Innovation and the inherent technological development call also for a historical perspective on the emergence of labor-saving (or labor-friendly) technologies and its co-movements with the economic cycle. Staccioli and Virgillito (2021) recently disputed the view of those co-movements and demonstrated that innovation waves follow a process of technological constellations instead of a dominant (general purpose) technology.

The innovation literature focuses mainly on the final employment change but we may ask if employment dynamics show a pattern of persistence or is a one-time event associated with innovation. Ciriaci et al. (2016) show how innovative, SME (and younger) firms have a higher probability of experiencing persistent job creation. Bianchini and Pellegrino (2019) arrive to similar results when firms, especially SMEs, systematically conduct product innovation activities.

[2] For example, Baffour et al. (2020); Balsmeier and Woerter (2019); Barbieri, Piva, and Vivarelli (2019); Van Roy, Vértesy, and Vivarelli (2018).

Persistent job creation does not imply necessarily longer job duration. It will still depend on the type of labor demanded by firms, especially considering the skills dimension.

Technological change is usually considered to be skill-biased, increasing the demand for skilled workers and changing the skills distribution in the labor market (Autor, Katz, and Krueger 1998; Berman, Bound, and Griliches 1994), owing to capital-skill complementarities (Griliches 1969). If skilled workers are better able to learn how to use new technologies and are more capable of producing new knowledge (Bartel and Lichtenberg 1987; Doms, Dunne, and Troske 1997), the demand for skills in innovative environments increases. Since the end of the 1990s, a new pattern emerged in the demand for skills (Acemoglu and Autor 2011; Autor, Katz, and Kearney 2006; Goos and Manning 2007; Goos, Manning, and Salomons 2014), with the routine-biased technological change (Autor, Levy, and Murnane 2003) where automation starts to replace workers typically in the middle of the wage-skills distribution leading to a polarization of the labor market (Cirillo et al. 2021, Fonseca, Lima and Pereira 2018).

Hazards of job separation are tightly linked to general human capital (Becker 1993) and to firm-specific human capital (Farber 1999). But knowledge-intensity also influences separation rates and worker mobility in part through skills — workers in more innovative industries have lower separation rates (Greenhalgh and Mavrotas 1996). Knowledge-intensive industries have higher demands for firm-specific human capital, often acquired through on-the-job training (Bartel and Sicherman 1998). Manufacturing plants using more advanced technologies also hire more qualified workers (Doms, Dunne, and Troske 1997) and firms that adopt information technologies will use more skilled labor (Bresnahan, Brynjolfsson, and Hitt 2002). Workers in innovative industries receive more on-the-job training and therefore have lower turnover rates (Mincer 1989). Furthermore, technology-adopting firms are more likely to provide training that allows workers to further explore said technology, making these firms more productive than those that do not train workers (Boothby, Dufour, and Tang 2010). Less-skilled and less-educated individuals in innovative companies, however, are not as likely to receive training (Bartel and Sicherman 1998), accentuating the skill gap. Thus, low-skill workers may expect higher separation rates and shorter job duration in knowledge-intensive companies.

2.2. Firm size, technology adoption, and innovation

Large firms are more likely to adopt new technologies from early advanced manufacturing technology (Arvanitis and Hollenstein 2001; Dunne 1994), to information and communication technologies (Lucchetti and Sterlacchini 2004) and, more recently, industrial robots (Acemoglu and Restrepo 2020).[3] Mansfield (1963) is one of the earliest works to study the relationship between firm size and time to adoption of a technology, and generally finds that larger firms are quicker to adopt new technologies, although this might not hold in every industry. In another early study, Romeo (1975) finds that firm size increases not only the probability of adoption of new technologies but also decreases time to adoption.

However, large firms' higher levels of bureaucracy and resistance to change associated with sunk resources and human capital in the old technology might slow down adoption (Hall and Khan 2003). Indeed, while the findings in the literature are mostly consensual about the sign of the relationship between size and technology adoption, J. Meyer (2011) finds no significant effect of the number of employees on adoption of new or improved technologies in small and medium-sized service firms, raising the question of whether the relationship can only be found in larger firms.

[3] See Hall and Khan (2003) for extensive reviews of technology adoption and firm size. Stoneman and Battisti (2010) review the literature on technology adoption and diffusion at the international, inter-industry, intra-industry, intra-firm and household levels.

An important mechanism through which large firms will adopt more technology is the higher quality of their employees (Geroski 2000) and the evidence presented would lead one to conclude that technology-skill complementarities will further expand the size-advantage in technology adoption that larger firms enjoy.

R&D-intensive firms also tend to adopt more technology (e.g., Romeo 1975; Gómez and Vargas 2012). As Cohen and Levinthal (1989) put it, expenditure in research and development generates new knowledge for firms, but also increases the firm's ability to acquire and use information that already exists and that can be sourced outside the firm. This ability would also, therefore, favor the adoption of new technologies. The interplay between innovation and technology adoption could potentiate the size-premium of larger firms (especially for those that are more knowledge-intensive) if these firms are also more innovative.

However, there is much less consensus on whether small or large firms are more innovative or even if there is any strong link between size and innovation (Acs and Audretsch 1988; Cohen 2010; Cohen and Klepper 1996; Pavitt, Robson, and Townsend 1987; Tsai and Wang 2005). High fixed R&D costs imply a strong financial commitment that small firms might not be willing to make given the pressure that a failed R&D project could place on firm survival (Rammer, Czarnitzki, and Spielkamp 2009). Small firms may lack the resources to sustain several R&D projects to hedge against the risk of failure (Revilla and Fernández 2012).

As Fisher and Temin (1973) argued, a size advantage in innovation inputs (R&D spending or employees' skills) does not necessarily imply a size advantage in innovation outputs (patents, new processes or products). This distinction is central to explain the relationship between firm size and innovation, a relationship that may depend also on the technological regime (Revilla and Fernández 2012) or the technological dynamics of the economic environment (Revilla and

Fernández 2013). Moreover, Audretsch, Kritikos, and Schiersch (2020) show the importance of highly-skilled employees (similar to that of R&D) for innovation performance in knowledge-intensive services microfirms. The presence of high-skill workers and their involvement in R&D activities coupled with training are essential internal sources for innovation and growth (Molodchik, Jardon, and Yachmeneva 2021), complementarity with external sources as cooperation activities or presence in external markets. Small businesses are known to have a lower probability of survival (Geroski, Mata, and Portugal 2010), as do less technological and less innovative firms (Cefis and Marsili 2012; Ortiz-Villajos and Sotoca 2018; Yang, Bossink, and Peverelli 2017). Firm growth and changes of survival depend on its own strategy in choosing and combining resources, and the external conditions — the functioning of the input and output markets. Larger, high-tech and high-growth firms have higher changes of success (Mogos, Davis, and Baptista 2021), even if achieving sustainable (high-)growth is not obvious (Hölzl 2014).

Combining the fact that large firms adopt more technology and value skills more, and that technology and knowledge intensive firms value skills more, we would expect to see an even larger premium for skills in larger technology and knowledge intensive firms, that translates into more stable jobs. In the same vein, the demand for innovation inputs increases with firm size. Skilled labor is an input for innovation, to be combined with R&D and other sources of knowledge creation. If indeed demand for R&D increases with firm size, we will expect R&D and innovation to be another driver of skill premiums – longer job duration – associated with size.

2.3. Firm size and job duration

Evans and Leighton (1989) find sorting of workers into firm size classes based on both observed and unobserved ability, and that education and indicators of stability contribute to working in a large company. Abowd, Kramarz, and Margolis (1999) present strong evidence of large firms hiring workers with higher unobserved ability. The higher quality of labor is also related to capital-skill complementarities (Griliches 1969), given that larger organizations have a greater intensity of capital use and adopt more advanced technologies (Dunne 1994; Idson and Oi 1999; Troske 1999). High-skilled workers are matched together in large employers through a sorting process (Kremer 1993) or self-select to jobs in the best firms (Idson and Feaster 1990).

Employer size is positively linked to tenure and negatively related to worker turnover (Oi 1990). One natural justification is that larger organizations last longer (Brown and Medoff 2003). If smaller businesses are more likely to fail, the average tenure in small businesses will be smaller because the working spells are interrupted when the company closes. Idson (1996) suggests that firm survival is also indirectly associated with turnover through training. Companies that are more likely to survive have longer average job durations, which, in turn, raise the expected returns from on-the-job training with an additional positive effect on employment duration (Mincer 1989). The higher quality of labor found in larger employers will determine job duration, owing to the increased productivity of skilled workers, and to the higher propensity to receive training (Barron, Black, and Loewenstein 1987), the complementarities between ability and training (Haber 1991) and economies of scale in training (Black, Noel, and Wang 1999). Internal labor markets present in large employers may also reduce turnover by offering more opportunities for internal promotion, rather than having workers look for opportunities outside of the company (Idson 1996).[4]

In conclusion, the literature has provided extensive evidence that the demand for skills is greater in both knowledge-intensive and large firms. This suggests that knowledge-skill

[4] See also the recent discussion by Kotey and Koomson (2021) on the heterogeneous effects of different flexible work arrangements across firm size.

complementarities may be enhanced by firm size, reflecting a higher premium for skills for workers in large knowledge-intensive firms. Small knowledge-intensive firms face two opposed effects: knowledge-skill complementarities that increase the returns to skills, and a small-size penalty in hiring and retaining skilled workers; the premium in larger firms might be so substantial that smaller knowledge-intensive firms cannot compete for skilled workers. To our knowledge, the link between employer size, knowledge intensity and job duration has not been investigated in previous studies. We aim to fill such gap with this work.

3. Data on knowledge intensity, firm size and job duration

To study the relationship between knowledge intensity, firm size and job duration, we use *Quadros de Pessoal*, a mandatory yearly survey submitted to the Portuguese Ministry of Employment and Social Security by every private company with at least one employee. The longitudinal linked employer-employee data set includes information on workers' gender, age, job level, level of education, tenure in the firm and wages. For firms, it includes information on the number of employees, age, legal structure, industry, and region. Our sample covers the period from 2003 to 2018, with an average of 2.8 million workers and 300,000 firms per year.

3.1. Sample construction and identification strategy

Our sample is composed of paid employees who are at least 16 years old. We also censor workers once they reach the age of 55 to exclude job separations caused by retirement.[5] To properly identify a working spell's initial conditions, we only look at job relationships that start during the observation period. By doing so, we also remove issues that may originate from left-censored data.

[5] In Portugal, a worker may retire as soon as the age of 55, under some contractual schemes.

Our identification strategy relies on studying workers displaced by firm closure as in Neal (1995), Castro Silva and Lima (2017), and Goos, Rademakers, and Röttger (2021). Firm closure leads to involuntary job separations. Building a sample of displaced workers may mitigate selection effects that might be present when a new job spell starts, namely voluntary switches originating from unobserved heterogeneity (Goos, Rademakers, and Röttger 2021). By construction, all employees previously present in a firm in the year of closure are included in the initial sample. We allow a three-year window after firm closure for workers to find a job, giving workers of different skill levels and different job-finding rates some time to find a new job such that there is enough heterogeneity in the ability level of sampled workers. Despite this window, our sample leaves out workers who take longer to find employment as well as those who have been permanently dismissed and do not return to the labor market. This selection is a limitation of our identification strategy that we do not address.

A working spell is observed from the start until job separation occurs or the observation is censored. We have no data on the reasons for separation, so we cannot discriminate between voluntary and involuntary exits. We only consider the first working spell after displacement and workers do not return to the sample once a job separation occurs; multiple spells would imply a progressively smaller number of individuals who experience several firm closures across their careers.

The year in which a company closes is also censored. As discussed in Section 2, small, less technological and less innovative firms have a lower probability of survival. Including the year of firm closure would systematically increase the likelihood of job separation for workers in small and less technological organizations, for reasons that are likely to be unrelated to an employee's productivity.

With these restrictions, our working sample is composed of 542,891 worker-year observations of 210,620 individuals employed in 90,518 firms.

3.2. Main variables and descriptive statistics

We categorize firms as knowledge-intensive if they operate in a knowledge-intensive services or if they operate in a high-technology or medium high-tech manufacturing, according to Eurostat's industry-level (NACE Rev. 2 codes) definition.[6] We define two firm-size categories based on the number of employees: firms with fewer than 50 workers (small firms); companies with 50 or more employees (medium and large firms).

The data set includes a job-level variable corresponding to the firm's classification of employees according to their hierarchical position, experience, task complexity, and degree of responsibility. The variable has eight levels defined by law, which is explicit regarding the kind of skills needed in each level.[7] To make the classification more tractable, we synthesize the variable into two categories according to the skill requirements of each job level. We classify as high-skilled the job levels corresponding to top management, managers, supervisors, team leaders and highly qualified professionals. According to law, these levels imply a high degree of autonomy, specialization in the tasks at hand and/or knowledge of management and coordination of the firm's activities. The remaining levels (qualified professionals, semi-qualified professionals, unskilled professionals, and trainees, apprentices and other entry or trial categories) are classified as not

[6] See Table A1 in the Appendix for the Eurostat classifications according to industry codes.

[7] See Table A1 in Baptista, Lima and Preto (2012) for a description of each level according to Decree-Law 121/78 of July 2.

high-skilled. Workers in these levels have well defined tasks, have lower qualifications levels, are not specialized and do not engage in management or coordination tasks.

Table 1 shows the mean and standard deviation of the more relevant variables, as well as the distribution of workers by size category and knowledge intensity. In our sample, 63% of the workers are in a small-sized firm, and mostly in less knowledge-intensive industries (78%). The proportion of workers in knowledge-intensive firms is higher in firms with 50 or more employees — about 37% of workers in firms with at least 50 employees are employed in knowledge-intensive industries, compared to only 14% in small firms. The share of workers with college education is much lower in less knowledge-intensive companies (8% vs. 31%) and in small companies (11% vs. 17%). A similar pattern is observed regarding the high-skills variable, pointing to a large skills gap between knowledge intensity categories. The average working spell is longer in small firms (2.63 years versus 2.50 years in larger firms), but there is no statistically significant different between both levels of knowledge intensity. The fact that workers in smaller companies are about 1.6 years older might partly explain the difference in tenure and education between both size categories. More than half of the workforce in knowledge-intensive firms in our sample is female (52%), but the distribution of women is about the same in small and large firms (around 44%), in line with the distribution in the Portuguese economy.

Regarding the previous job before displacement, workers currently in large firms and in knowledge-intensive industries are more likely to have come from a different sector; these firms might have more diversified activities which makes it easier to accommodate a broader set of previous labor market experiences. A small share of workers in small and less knowledge-intensive firms came from a job in a large firm (10%) or from a knowledge-intensive industry (14%); this share is considerably smaller compared to the quota of workers in large firms (41%) and knowledge-intensive industries (33%). This suggests a strong segmentation between size categories and knowledge classes: workers displaced from small or less knowledge-intensive firms might struggle to access the arguably better jobs in large or knowledge-intensive companies. Knowledge-intensive firms are on average much older and larger than their counterparts, both in terms of the number of employees and of number of establishments.

Table 1: Descriptive statistics for displaced workers

	All displaced	< 50 employees	≥ 50 employees	Less knowledge intensive	Knowledge intensive
In firm with fewer than 50 employees	0.63	—	—	0.70	0.39
	(0.48)			(0.46)	(0.49)
In knowledge-intensive industry	0.22	0.14	0.37	—	—
	(0.42)	(0.34)	(0.48)		
College	0.13	0.11	0.17	0.08	0.31
	(0.34)	(0.31)	(0.38)	(0.27)	(0.46)
High-skilled job	0.15	0.15	0.17	0.11	0.31
	(0.36)	(0.35)	(0.37)	(0.31)	(0.46)
Tenure	2.58	2.63	2.50	2.58	2.56
	(2.40)	(2.38)	(2.43)	(2.39)	(2.45)
Age	34.83	35.44	33.81	35.03	34.14
	(9.10)	(9.23)	(8.79)	(9.33)	(8.21)
Female	0.44	0.44	0.45	0.42	0.52
	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)
Part-time worker	0.06	0.04	0.09	0.06	0.06
	(0.23)	(0.19)	(0.28)	(0.23)	(0.25)
Fixed-term contract	0.53	0.48	0.61	0.51	0.58
	(0.50)	(0.50)	(0.49)	(0.50)	(0.49)
In manufacturing firm	0.17	0.17	0.16	0.20	0.07
	(0.38)	(0.38)	(0.37)	(0.40)	(0.25)
Came from different sector	0.54	0.48	0.65	0.50	0.70
	(0.50)	(0.50)	(0.48)	(0.50)	(0.46)
Previous firm ≥ 50 employees	0.21	0.10	0.41	0.18	0.33
	(0.41)	(0.30)	(0.49)	(0.39)	(0.47)
Previous firm was knowledge-intensive	0.20	0.14	0.29	0.10	0.53
	(0.40)	(0.35)	(0.46)	(0.30)	(0.50)
Came from non-employment	0.50	0.49	0.51	0.48	0.55
	(0.71)	(0.71)	(0.71)	(0.70)	(0.73)
Legal structure: corporation	0.22	0.06	0.49	0.20	0.29
	(0.41)	(0.23)	(0.50)	(0.40)	(0.46)
Number of employees	804.65	14.38	2136.56	570.56	1623.99
	(2,975.64)	(12.67)	(4,577.22)	(2,830.04)	(3,309.13)
Number of establishments	11.11	1.28	27.68	9.97	15.10
	(52.68)	(1.12)	(83.74)	(47.95)	(66.50)
Firm age	14.17	9.40	22.22	12.53	19.92
	(23.21)	(12.85)	(32.64)	(14.52)	(40.55)
Number of workers	210,620	132,188	78,432	163,817	46,803
Number of observations	542,891	347,034	195,857	422,900	119,991
Number of firms	90,518	83,323	9,651	76,148	14,370

Note: Mean values and standard deviations (in parentheses). Statistics computed using the last observation of each worker.

Finally, to study job duration across firm size, the heterogeneity of firms' personnel policies should be accounted for. Some firms will have human resources practices that favor worker retention while others will be more prone to worker turnover. These practices will be related to wage policies translated into different wage levels, wage profiles and promotion policies along specific hierarchical setups (Bloom and Van Reenen 2007). In order to have a (simple) measure of firms' personnel policies, we run a wage regression for all firms hiring the workers in our sample. We include only those years that precede the hiring, thus avoiding including workers present in the sample under study.[8] The regression includes firm's fixed effects to capture firms' wage practices such as paying above or below market competitors after controlling for all observable worker and firm characteristics. The coefficients for this simple wage regression are displayed in Table A3 in Appendix. As expected, workers with more general human capital (years of education, age) and firm specific human capital (firm tenure) will earn higher wages, and the hierarchical level also strongly determines wages. Because we use a fixed effects approach, the firms' characteristics included as controls have little significance given their very small variability across time.

Following Abowd, Kramarz, and Margolis (1999)'s interpretation, the firm fixed effect would also capture part of the firm's ability to hire individuals with higher unobserved ability. It is a one-dimensional measure of firm's personnel policies, adding information to control for firms' heterogeneity that may affect job duration. After running the regression, we compute the estimated firm fixed-effect and partition its distribution into quartiles to classify the firm's relative position. For new firms or for any firm with less than two observed years before hiring a worker in our sample, we are not able to compute a fixed-effect and classify these firms as "No firm fixed effect".

[8] The sample for the fixed effects wage regression covers each company's history since 1996 up to the year before hiring a worker belonging to our main sample. The regression controls for workers' years of education, gender, age, hierarchical level, occupation, and tenure in firm, the firm's region, industry, sales, legal structure, presence of foreign equity, and year dummies.

It corresponds to about 35,000 firms (mostly small, less knowledge-intensive) employing 34% of the workers in our sample.

Table 2 presents the resulting figures of this exercise. The proportion of workers in high-paying firms (3rd and 4th quartiles of the firm fixed effect) is considerably higher in firms with 50 or more workers and in knowledge-intensive industries. This suggests that these firms are more willing to pay above market wages. Workers in small firms might therefore find worse compensation conditions, reflecting an incapacity to retain skilled workers in small firms. The share of workers in small high-paying (4th quartile) firms is higher in knowledge-intensive industries (10.5% versus 6.0% in less knowledge-intensive industries — not shown), which might indicate that these firms are somewhat more competitive wage-wise, though the gap to knowledge-intensive firms with at least 50 workers is large — 34.7% of the workers in larger knowledge-intensive firms are in firms paying above market wages.

Table 2: Descriptive statistics for displaced workers: firm fixed effects

	All displaced	< 50 employees	≥ 50 employees	Less knowledge intensive	Knowledge intensive
Firm fixed effect 1st quartile	0.18	0.22	0.12	0.19	0.14
	(0.39)	(0.41)	(0.32)	(0.40)	(0.34)
Firm fixed effect 2nd quartile	0.17	0.16	0.17	0.17	0.17
	(0.37)	(0.37)	(0.38)	(0.37)	(0.38)
Firm fixed effect 3rd quartile	0.17	0.11	0.27	0.16	0.19
	(0.37)	(0.31)	(0.44)	(0.36)	(0.40)
Firm fixed effect 4th quartile	0.14	0.07	0.28	0.11	0.25
	(0.35)	(0.25)	(0.45)	(0.32)	(0.43)
No fixed effect	0.34	0.44	0.16	0.37	0.24
	(0.47)	(0.50)	(0.37)	(0.48)	(0.43)

Note: Mean values and standard deviations (in parentheses). Statistics computed using the last observation of each worker.

Our descriptive results suggest that workers in larger and knowledge-intensive companies are, in general, more skilled, although there seems to be no *a priori* evidence that the skill advantage translates to longer job durations, as those employed in small and less knowledge-intensive firms have longer tenures and smaller rates of job separations.

4. Empirical model

Our objective is to characterize how knowledge intensity influences the relationship between human capital and the hazard of job separation, and how this relationship changes in firms of different sizes. We propose to estimate different specifications of discrete-time proportional hazards models accounting for unobserved heterogeneity (Lancaster 1979), interacting the main variable of interest with the firm size categories and the knowledge-intensity classes. The hazard of job separation is the probability of a job separation occurring in moment t, conditional on having stayed at the job for t periods.

The proportional hazards model has the following form:

$$\lambda_i(t) = \theta_i \lambda_0(t) \exp\left(\mathbf{z_i}(\mathbf{t})' \boldsymbol{\beta}\right) \tag{1}$$

where λ_i is the hazard of job separation for worker i with tenure t, θ_i is the unobserved heterogeneity random variable for worker i, $\lambda_0(t)$ is the baseline hazard function of tenure. The baseline function represents the time-dependence of the hazard when the remaining explanatory variables are at their base levels. $\boldsymbol{z_i}(\boldsymbol{t})$ is the vector of explanatory variables for worker i and $\boldsymbol{\beta}$ is the vector of parameters to be estimated.

We cannot determine exactly when a job spell ends within the year because of interval-censoring — our data are yearly. This censoring may result in tied survival times, which could lead to biased estimates. To address this issue, Allison (1982) suggests the use of a discrete-time model that handles tied failures and interval-censoring. Therefore, we choose Prentice and Gloeckler (1978)'s proportional hazards model, obtained by rewriting Equation 1 to follow a complementary log-log formulation:

$$\lambda_i(t) = 1 - \exp[-\exp(\mathbf{z_i(t)}'\boldsymbol{\beta} + c(t)] \tag{2}$$

where $c(t)$ is a function of tenure that relates to the baseline hazard in the tth year of tenure.

Misspecifying the functional form of the baseline hazard leads to erroneous parameter estimates (van den Berg 2001). Nonetheless, to our knowledge, economic theory provides no suggestions on which form the baseline hazard function should take. We choose a flexible specification with a piecewise-constant function representing the baseline, where in each yearly segment the hazard is assumed to be constant (B. Meyer 1990). Van den Berg (2001) argues that this specification might be the most useful when using single spell data such as ours.

As described in Section 3.2, we have at our disposable a large set of independent variables that account for some sources of heterogeneity at the worker level (college, high-skilled, tenure, age, gender, part-time job, fixed term contract, recent experience in a large firm, in a knowledge-intensive industry, a different industry than the current one, as well as if any time was spent in non-employment between job spells), and the firm level (size category, in a knowledge intensive industry, manufacturing firm, number of establishments, age and legal structure) as well as controls for regional effects and macroeconomic trends. Despite this, unobserved heterogeneity may persist. In job duration models, unobserved heterogeneity arising from omitted variables or measurement error can deeply influence parameter estimates (Farber 1999; van den Berg 2001). We use a model with random effects following a Normal distribution to partially account for the presence of unobserved heterogeneity. In the duration analysis context, these random effects are often called frailty.[9] Our choice falls on the Normal distribution because it allows for the

[9] To our knowledge, an unbiased discrete-time proportional hazards fixed effects estimator does not exist. Including an individual-level fixed effect into our binary model would result in a selected sample which excludes all

computation of average marginal effects, which are easier to interpret than hazard ratios or parameter coefficients, especially in models with interactions (Buis 2010). Nicoletti and Rondinelli (2010) downplay the magnitude of the bias that may originate from a misspecification of the unobserved heterogeneity distribution. Additionally, the piecewise-constant function specification we choose for the baseline hazard function also alleviates the bias (Dolton and Klaauw 1995).

Wide empirical evidence shows that more capable workers sort themselves into larger organizations (see, for example, Abowd, Kramarz, and Margolis 1999; Evans and Leighton 1989). The results may be biased if one fails to properly account for this self-selection. In the size-wage differentials literature, a commonly proposed strategy is to estimate two-step models in the spirit of Heckman (1979), in which the first step consists of estimating an ordinal probability model for the likelihood of being employed in one of the size categories (see, for example, Idson and Feaster 1990). Unfortunately, to our knowledge, there are no convenient methods of estimating discrete-time duration models that consider the non-random selection of workers in this manner.

We follow two complementary strategies to address this issue. First, as explained in Section 3.1, we select a sample of displaced workers to guarantee to the extent possible that we have a random sample of workers finding a job. By including all workers employed by a firm in the last year before exiting the market, the sample is not overpopulated by voluntary firm switching. The second strategy follows Solon, Haider, and Wooldridge (2015) who argue that sample weights

individuals who do not experience a job separation during the period of analysis (35.5% of workers in our sample), because of no variation in the dependent variable. Additionally, a fixed effects method would exclude workers with one-year durations (49.5% of workers in our sample) because of demeaning. Allison and Christakis (2006) discuss the consequences of using conditional logistic regression with fixed effects for single-event analysis and propose an alternate method. This method, however, is impractical if researchers are interested in studying the effect of multiple variables, cannot be used to estimate the effect of covariates that are monotonic with time, and seems very sensible to omitted variables. For these reasons we prefer a random effects (frailty) approach.

may lead to improvements in the presence of endogenous sampling. Therefore, we obtain, from a probit model, the predicted likelihood of each individual being employed in a small firm. The inverse of this predicted probability is then used as a weight in the hazard models. Thus, for example, a worker whose observed characteristics (e.g., high-skilled) make her unlikely to be employed in a small company will contribute more to the likelihood function of the job separation models. If high-skill workers are oversampled in large firms, we cannot correctly estimate the relative contribution of human capital to the hazard of job separation. Balancing the sample with weights lessens the problem.

5. Results

We proceed by estimating discrete-time hazard models with random effects for job duration using the sample of displaced workers. We weight each worker by her predicted probability of being employed in a small firm (results of the probit model in Appendix B). Our first objective is to analyze, in small and large firms, the relationships between job duration and human capital variables such as tenure, education, and skill level. Furthermore, we want to study how a measure of the firms' human resource management practices impacts the hazard of job separation. We are also interested in understanding if the relationships with human capital and human resources practices differ in the presence of more knowledge intensity. To achieve this, we estimate a model for each human capital variable interacted with a dummy variable for size category and knowledge-intensity class (three-way interaction). Our expectations are that, in terms of job duration, the returns to skills are smaller in firms with fewer than 50 workers, and that the knowledge-skill complementarity is more important in larger firms. We also expect that better human resource practices should allow small firms to close the gap against larger firms.

5.1. The base job duration model

We start with the base model, without interactions with firm size and knowledge intensity. The model includes the main human capital variables (college education, high-skilled job, tenure), and additional controls for worker characteristics such as gender, second-degree polynomial of age at entry, and indicators for part-time work, fixed-term contract, a change of sector (two digits) after displacement, a recent experience in a large firm or a knowledge-intensive firm, and if the worker spent time in non-employment.[10] On the employer side, we include controls for legal structure, the logarithm of the number of establishments, and of the company's age when the worker joined, as well as controls for region. Because the knowledge intensity variable is defined at the industry-level, we do not include further controls for industry. Nonetheless, we incorporate a categorical variable to distinguish between services and manufacturing firms. Controls for the yearly regional unemployment rate and the Gross Domestic Product growth rate account for macroeconomic trends. We also interact GDP growth rate with the knowledge intensity indicator to attempt to partially capture temporal shocks that may have different effects in different sectors. Given the strong relationship between education and skills, we estimate three specifications according to the use of the education variable (College), skill level (High-skilled job) or both variables simultaneously.

Results in Table 3 show that both college education and high-skills decrease the hazard of job separation, but when included together the marginal effect of college decreases in a sizeable manner, as expected given that college graduates are concentrated in high-skill jobs. Being

[10] We accumulate all tenures equal to or above five years in a single level of the tenure variable for the sake of parsimony. In our sample, only about 8% of job separations occur on the fifth year of tenure or later, compared to 61% in the first year, or 18% in the second year.

employed in a small firm decreases the hazard of job separation, but workers in a knowledge-intensive industry observe a small increase of the hazard. The increasingly more negative marginal effects of tenure reveal a negative duration dependence, reflecting that the accumulation of firm-specific human capital decreases the hazard of job separation.

While age at entry exhibits decreasing marginal returns, the average marginal effect is negative, with older workers having smaller probabilities of job separation on average. Female workers and workers employed in manufacturing face lower hazards, but workers with a fixed-term contracts or working part-time have greater hazards of separation, reflecting their weaker formal attachment to the firm. With regards to the previous employment experience, we see that workers displaced from firms with 50 or more employees, as well as those who spent time in non-employment between jobs experience a higher likelihood of job separation, and those changing sectors are penalized for a lack of industry-specific human capital. The opposite is true for those coming from a knowledge-intensive industry.

We also include other firm-level controls, complementary to firm size: holding fixed the size category, a larger number of establishments translates into greater hazards, but the risk of job separation is smaller in older firms and corporations (public limited companies).

The indicators for the firm fixed effect quartiles, which represent a measure of the level of firms' wage practices, have progressively more negative marginal effects compared to the base level.[11] The more generous the wage policy of the firm the less likely it is for a job separation to

[11] See Sub-section 3.2 for more detail on this variable.

occur. This is especially true for workers in firms at the top of the distribution of the fixed effect, who enjoy a reduction of the hazard of about 10 percentage points (p.p. henceforth).

Table 3: Average marginal effects on the hazard of job separation:
Models without interactions with knowledge intensity and size category

	Education	Skill Level	Education and Skill level
In firm with fewer than 50 employees	-0.043***	-0.039***	-0.040***
	(0.001)	(0.002)	(0.002)
In knowledge-intensive industry	0.004***	0.011***	0.012***
	(0.001)	(0.001)	(0.001)
College	-0.050***		-0.011***
	(0.002)		(0.002)
High-skilled job		-0.088***	-0.083***
		(0.002)	(0.002)
Tenure = 2	0.013	0.008	0.004
	(0.009)	(0.009)	(0.009)
Tenure = 3	-0.022**	-0.025**	-0.029***
	(0.010)	(0.010)	(0.010)
Tenure = 4	-0.037***	-0.039***	-0.043***
	(0.010)	(0.010)	(0.010)
Tenure ≥ 5	-0.056***	-0.055***	-0.059***
	(0.011)	(0.011)	(0.011)
Age at entry	-0.002***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Female	-0.039***	-0.043***	-0.042***
	(0.001)	(0.001)	(0.001)
Part-time worker	0.097***	0.095***	0.095***
	(0.002)	(0.002)	(0.002)
Fixed-term contract	0.122***	0.120***	0.120***
	(0.001)	(0.001)	(0.001)
In manufacturing firm	-0.098***	-0.100***	-0.101***
	(0.002)	(0.002)	(0.002)
Came from different sector	0.023***	0.021***	0.021***
	(0.001)	(0.001)	(0.001)
Previous firm was ≥ 50 employees	0.034***	0.034***	0.034***
	(0.001)	(0.001)	(0.001)
Previous industry was knowledge-intensive	-0.030***	-0.027***	-0.026***
	(0.001)	(0.001)	(0.001)
Came from non-employment	0.003**	0.002*	0.002*
	(0.001)	(0.001)	(0.001)
Legal structure: corporation	-0.008***	-0.006***	-0.005***
	(0.001)	(0.001)	(0.001)
Log number of establishments	0.001**	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
Log firm age at entry	-0.013***	-0.014***	-0.013***
	(0.001)	(0.001)	(0.001)
Firm fixed effect: 2nd quartile	-0.020***	-0.020***	-0.020***
	(0.002)	(0.002)	(0.002)
Firm fixed effect: 3rd quartile	-0.033***	-0.033***	-0.033***
	(0.002)	(0.002)	(0.002)
Firm fixed effect: 4th quartile	-0.105***	-0.103***	-0.102***
	(0.002)	(0.002)	(0.002)

Log of Normal Variance (log σ^2)	-0.516***	-0.428***	-0.413***
	(0.055)	(0.054)	(0.053)
Number of observations	542,891	542,891	542,891
Number of workers	210,620	210,620	210,620
Log likelihood	-511,355.6	-510,176.0	-510,157.8
Log likelihood for model with $\sigma^2 = 0$	-511,755.0	-510,626.9	-510,616.2
p-value for LR test of $\sigma^2/(1+\sigma^2) = 0$	0.000	0.000	0.000

Notes: Standard errors in parentheses. Sample composed of previously displaced workers. Model is a cloglog with unobserved heterogeneity following a Normal distribution with variance σ^2, weighted by the inverse probability of being employed in a small firm. Regressions include controls for region, yearly GDP growth rate (and an interaction with knowledge intensity indicator) and regional unemployment rate. Worker's age is included in quadratic form. Marginal effects are calculated at observed values of other variables, with respect to the random effect.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

5.2. Knowledge-skill complementarity across size categories

Figures 1 through 4 show the average marginal effects of our main independent variables obtained from the estimation models with interactions with firm size and knowledge intensity, in addition to all of the controls presented in Table 3.[12] The marginal effects of college education in Figure 1 reveal an education premium for workers in less knowledge-intensive industries, regardless of firm size. However, in knowledge-intensive industries, while college-educated workers in firms with 50 employees or more enjoy a much larger decrease in the hazard of job separation of about 9.1 p.p. compared to those without college education, workers with more formal human capital are penalized in smaller firms, as shown by the positive and significant marginal effect.

[12] See results in Tables C1 through C3 in Appendix C.

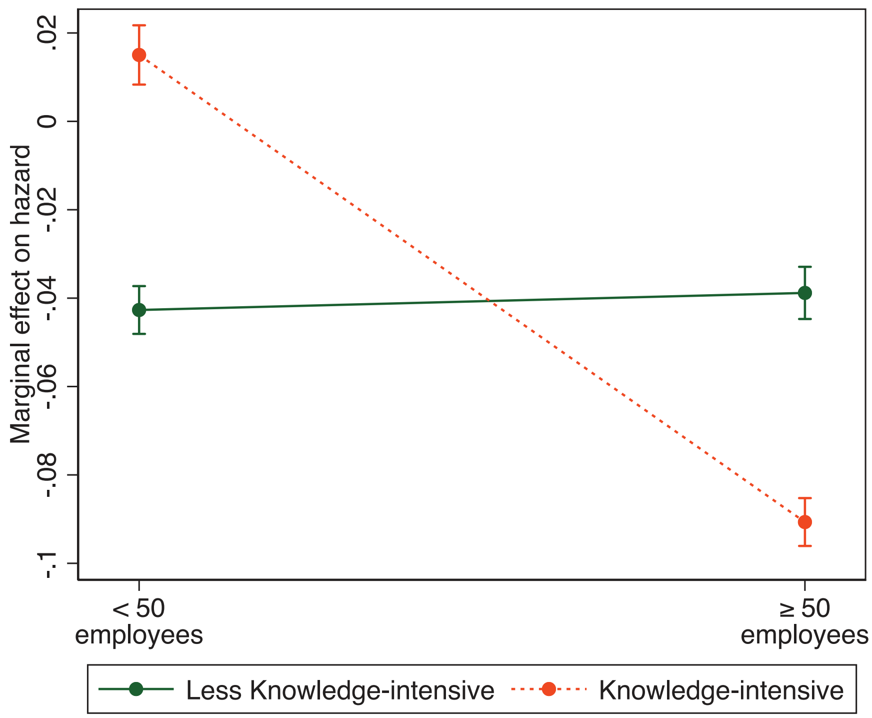

Figure 1: Average marginal effects of college education on hazard of job separation, by knowledge intensity and firm size (95% confidence interval). See first column of Table C1.

The marginal effects of holding a high-skilled job (Figure 2) tell a similar story. High-skilled workers in large knowledge-intensive firms experience considerably lower hazards of job separation than all other high-skilled workers. In small firms, high-skilled workers in less knowledge-intensive industries experience a decrease in the hazard of about 7.1 p.p. compared to non-high-skilled individuals, but in knowledge-intensive industries skilled workers have no significant advantage over less-skilled employees.

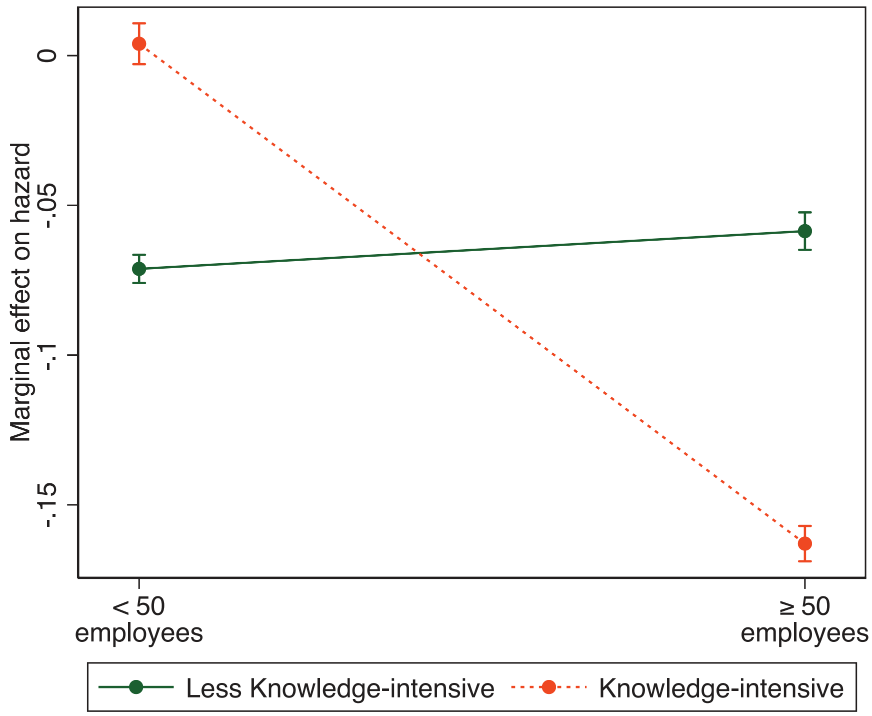

Figure 2: Average marginal effects of high-skilled jobs on hazard of job separation, by knowledge intensity and firm size (95% confidence interval). See second column of Table C1.

The results for college and high skills therefore reveal a knowledge-skill complementarity in firms with at least 50 employees but not in small firms. The fact that in small knowledge-intensive firms, college-educated workers or workers in high-skilled jobs experience no premium (or even a penalty) on the hazard of job separation suggests a mismatch of highly skilled individuals in such firms. These firms might not be able to offer employment conditions to retain more able workers who might be attracted to larger firms where their skills will find greater returns.[13]

[13] Because the college education and high-skilled jobs variables are highly correlated ($\rho = 0.53$), the marginal effects are obtained from specifications where these variables are included separately. See last column of Table C1 where both variables are included in the same specification — conclusions for high skills still hold, but the marginal effect of college education is reduced and is no longer significant in knowledge-intensive firms with at least 50 employees.

Tenure can be regarded as a measure of accumulation of specific human capital. By interacting tenure with the firm size and knowledge intensity categories we can understand how the returns to specific human capital accumulation vary between small and large firms in different knowledge intensity settings. The marginal effects of tenure on the hazard of job separation are plotted in Figure 3. In all four combinations of size and knowledge intensity, the marginal effects of tenure are negative and there is a general trend of decreasing marginal effects as tenure accumulates. This indicates that the hazard of job separation decreases with tenure, revealing the expected negative time-dependence of the hazard.

The accumulation of specific human capital appears to play a more important role in knowledge-intensive companies with at least 50 employees — after five years on the job, the hazard is about 19 p.p. lower than in the first year, which amounts to the largest reduction in all categories. The difference between the hazard in each adjacent year of tenure is also generally more negative in larger knowledge-intensive firms, meaning that an additional year in such a firm reduces the hazard by more than in any other category. Additionally, in firms with 50 or more workers the gap between the levels of knowledge intensity increases with every year of tenure, evidence of a complementarity between knowledge and firm-specific skills in that size class. In small firms there is no evidence of knowledge-tenure complementarity: the returns to tenure are similar in both classes of knowledge intensity.

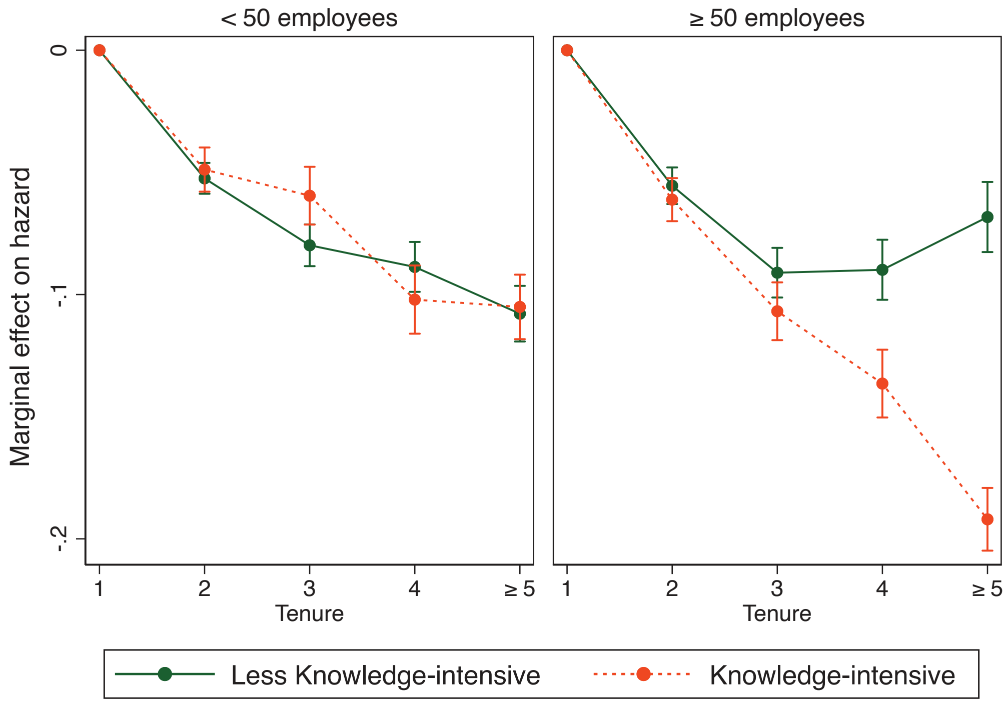

Figure 3: Average marginal effects of tenure on hazard of job separation, by knowledge intensity and firm size (95% confidence interval). See Table C2.

Figure 4 displays the marginal effects of the quartiles of the firm fixed effects (reflecting the firm's wage policy) by firm size and knowledge intensity.[14] This analysis intends to shed light on the influence of firms' ability to pay above market wage rates on the hazard of job separation, and how it varies across size categories and knowledge intensity levels. In every case, the marginal effects of the firm fixed effect quartiles are negative, showing that firms that have human resource practices that translate into a higher paying capacity than those in the first quartile are able to lower their workers' hazards of job separation, and are more capable of retaining employees.

[14] See Sub-section 3.2 for more details on the fixed effects.

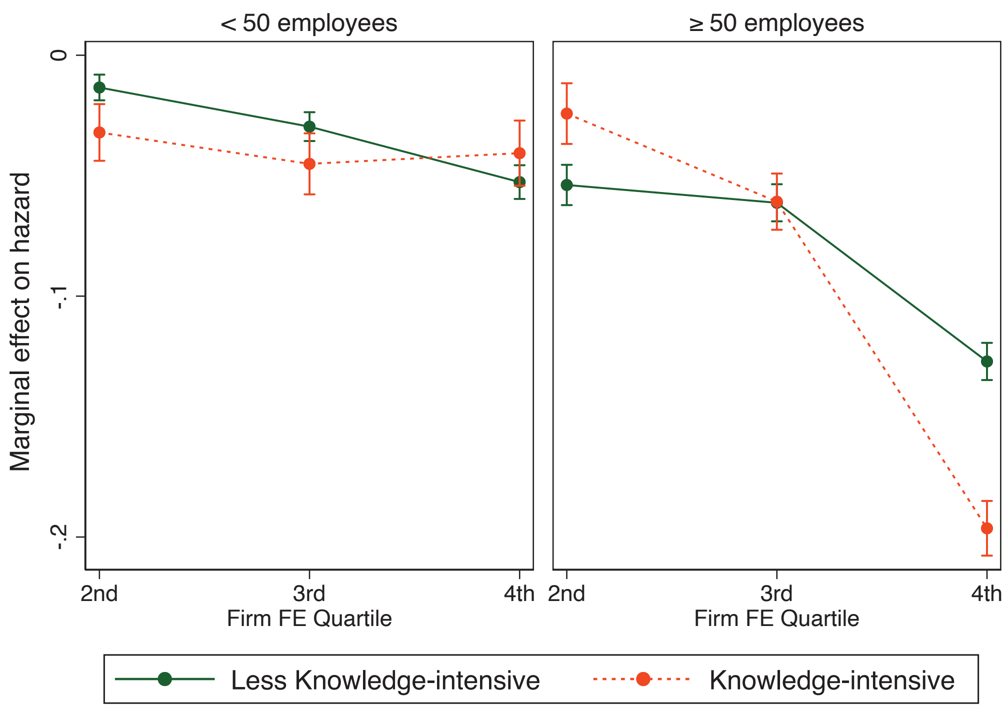

Figure 4: Average marginal effects of firm fixed effects quartile, relative to 1st quartile, on hazard of job separation, by knowledge intensity and firm size (95% confidence interval). See Table C3.

In small firms, while the marginal effect of the second quartile is more negative in knowledge-intensive firms, there is no significant difference between the knowledge intensity categories for the third and fourth quartiles. Looking more closely to small firms in knowledge-intensive industries, we see that the difference between the marginal effects of the second, third and fourth quartiles is small, and the fourth quartile's marginal effect is not significantly different from that of the second or third quartile. This would suggest that, although firms in the fourth quartile have better paying and hiring practices than other firms, these practices do not translate into lower job separation rates in knowledge-intensive firms with fewer than 50 employees. These results further compound with our previous findings where small firms in knowledge-intensive settings could not present a premium to college educated or other highly-skilled workers.

In firms with 50 or more employees, the marginal effect of the firm fixed effect becomes more negative the higher the quartile in both knowledge intensity categories. The marginal effect for the third quartile is not significantly different between knowledge classes. However, the marginal effect of the fourth quartile is much larger in absolute terms for knowledge-intensive firms (by about 7 p.p.). Additionally, the marginal effects of the second and third quartiles are similar in both small and larger firms, showing no particular size advantage in the success of personnel practices, with the exception of firms at the top of the distribution. As discussed previously, larger firms will tend to value worker skills more, especially those with more knowledge-intensive operations; the greater marginal effects of the firm's fixed effects could be a reflection of that, where these firms adopt better personnel practices in order to hire and retain a more skilled workforce.

For robustness' sake, we estimated our models in a sample with all workers starting a new job, and not just those displaced by firm closure. Our main conclusions hold for the unrestricted sample. The marginal effects for college and high skills in the unrestricted sample reveal smaller returns to skills. This is to be expected given that the unrestricted sample is on average more skilled than the sample of displaced workers (see Table A2). Returns to tenure, on the other hand, tend to be larger in the unrestricted sample — more skilled workers will experience more stable working relationships and additional years on the job further reduce the likelihood of job separation. We also ran all our regressions without the inverse probability weights and without accounting for a random effect. Our conclusions are robust in both cases.[15]

[15] Results for robustness checks are available upon request.

Our results suggest evidence of knowledge-skill complementarity in firms with 50 or more employees, but no evidence of complementarity in small firms. We see that, in general, education reduces the hazard of job separation, and the education premium is enhanced in the presence of greater knowledge intensity in large firms. We find a small but significant penalty to workers with a college degree in small knowledge-intensive firms. When considering a different measure of skills, we extract the same conclusion: the premium for high skills is considerably higher in larger knowledge intensive firms, but nonexistent in small firms. Furthermore, we find evidence of complementarity between knowledge intensity and the accumulation of firm-specific skills in larger firms but not in small firms, and a greater efficacy of personnel practices in knowledge intensive firms with at least 50 workers but no advantage in small firms in the same knowledge category. Our findings paint a picture of the inability of small knowledge-intensive firms to both hire and maintain a skilled workforce that is central to the firms' survival, success, and growth.

6. Conclusions

We studied how the knowledge-skill complementarity influences job duration in small and large companies by estimating different specifications of proportional hazards models for each size category. We concluded that the advantage high-skilled workers have over low-skilled, concerning the hazard of job separation, is greater in large organizations. Our analysis shows that the knowledge-skill complementarity positively influences job duration in large firms only, with knowledge intensity enhancing the education and skill advantage. The main conclusion from our results is that small firms struggle to retain high-skilled workers, being limited in their ability to create and handle knowledge.

We introduce a source of initial randomness to the sample of workers under study by considering only workers previously displaced due to firm closure. In the next step, our empirical model controls for endogenous sampling across employer size by balancing the hazard equations with weights obtained from the predicted likelihood of initial hiring by a small firm versus a large one. Additionally, all our duration models include Normally-distributed random effects (frailty) to further handle unobserved heterogeneity at the worker level. Despite these efforts, we recognize that some sources of unobserved heterogeneity may still persist: our random effects approach may only partially account for unobserved effects, and our sampling strategy excludes displaced workers that either take a long time to find employment or never find a new job.

In a knowledge-based society, skills are essential. Small firms are an important driver of employment creation, competitiveness and GDP growth through the introduction of new ventures with new products and processes. Small firms need to compete for high-skilled workers and to be able to offer conditions to retain it. If evidence shows that small firms are associated with lower job stability, then there is still space for public policy to intervene and find mechanisms to diminish the barriers to knowledge use and development, recognizing that human resources are the main assets of any new venture.

One possible extension to our work could consider the sorting of workers to firms of different levels of productivity, regardless of firm size. Our work could also be extended to study the employment history of workers, in particular to find how firm size and knowledge interact with the ability of workers to find jobs that allow for a stable career progression and skill acquisition. If small firms find it hard to retain skills, low-skill workers find it difficult to be hired and retained. The same could be said about young worker entering into the labor market. Moreover, large firms still use a substantial undifferentiated workforce in certain areas of the production process, applying hiring and pay practices that can be associated with precarious job conditions. As the knowledge-based economy is becoming established as the main agent for growth and prosperity in developed economies, benefits are not uniformly distributed, leaving (and possibly promoting) asymmetries in the labor and product markets. Thus, further research could delve into the duplet where (small) firms need the capabilities to grow, and workers strive to escape from disadvantageous segments of the labor market.

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Appendices

A. Supporting tables

Table A1: Knowledge-intensive industries

Code	Description
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
50	Water transport
51	Air transport
58	Publishing activities
59	Motion picture, video and television program production, sound recording and music publishing activities
60	Programming and broadcasting activities
61	Telecommunications
62	Computer programming, consultancy and related activities
63	Information service activities
64	Financial service activities, except insurance and pension funding
65	Insurance, reinsurance and pension funding, except compulsory social security
66	Activities auxiliary to financial services and insurance activities
69	Legal and accounting activities
70	Activities of head offices; management consultancy activities
71	Architectural and engineering activities; technical testing and analysis
72	Scientific research and development
73	Advertising and market research
74	Other professional, scientific and technical activities
75	Veterinary activities
78	Employment activities
80	Security and investigation activities
84	Public administration and defense; compulsory social security
85	Education
86	Human health activities
87	Residential care activities
88	Social work activities without accommodation
90	Creative, arts and entertainment activities
91	Libraries, archives, museums and other cultural activities
92	Gambling and betting activities
93	Sports activities and amusement and recreation activities

Note: Aggregation based on NACE codes Rev. 2. Knowledge-intensive industries include knowledge-intensive services and high-tech and medium-high-tech manufacturing.
Source: Eurostat.

Table A2: Descriptive statistics for unrestricted sample of workers

	All displaced	< 50 employees	≥ 50 employees	Less knowledge intensive	Knowledge intensive
In firm with fewer than 50 employees	0.54	—	—	0.61	0.37
	(0.50)			(0.49)	(0.48)
In knowledge-intensive industry	0.28	0.19	0.38	—	—
	(0.45)	(0.39)	(0.49)		
College	0.17	0.14	0.20	0.10	0.36
	(0.38)	(0.35)	(0.40)	(0.30)	(0.48)
High-skilled job	0.15	0.15	0.15	0.09	0.32
	(0.36)	(0.36)	(0.36)	(0.29)	(0.47)
Tenure	2.71	2.77	2.63	2.67	2.80
	(2.95)	(2.90)	(3.01)	(2.89)	(3.11)
Female	0.47	0.46	0.49	0.45	0.54
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Age	30.93	32.26	29.37	30.99	30.79
	(9.96)	(10.27)	(9.34)	(10.27)	(9.10)
In manufacturing firm	0.16	0.15	0.16	0.19	0.09
	(0.36)	(0.36)	(0.37)	(0.39)	(0.28)
Came from different sector	0.88	0.86	0.90	0.87	0.90
	(0.33)	(0.35)	(0.30)	(0.34)	(0.29)
Previous firm ≥ 50 employees	0.41	0.18	0.70	0.36	0.55
	(0.49)	(0.39)	(0.46)	(0.48)	(0.50)
Previous firm was knowledge intensive	0.07	0.05	0.09	0.04	0.15
	(0.25)	(0.22)	(0.28)	(0.19)	(0.35)
Number of workers	2,163,434	1,170,039	993,395	1,565,297	598,137
Number of observations	5,696,157	3,139,359	2,556,798	4,052,968	1,643,189
Number of firms	325,978	314,572	11,406	269,554	56,424

Note: Mean values and standard deviations (in parentheses). Sample includes workers displaced by firm closure from our main sample, and all other workers starting a valid working spell between 2003 and 2017. Statistics computed using the last observation of each worker.

Table A3: Wage regression with firm fixed effects

	Log wages
Years of education	0.010***
	(0.000)
Tenure	0.014***
	(0.000)
Tenure^2	-0.000***
	(0.000)
Female	-0.142***
	(0.003)
Job level: top manager	0.504***
	(0.014)
Job level: manager	0.347***
	(0.011)
Job level: supervisor/team leader	0.263***
	(0.007)
Job level: highly-qualified professional	0.166***
	(0.008)
Job level: semi-qualified professional	-0.106***
	(0.003)
Job level: non-qualified professional	-0.208***
	(0.007)
Job level: apprentice/intern/trainee	-0.148***
	(0.004)
Age	0.021***
	(0.001)
Age^2	-0.000***
	(0.000)
Constant	5.557***
	(0.026)
R^2 (within)	0.366
Number of observations	8,830,059

Notes: Robust standard errors in parentheses. Regressions include controls for worker's occupation, number of employees, sales, firm's legal structure, presence of foreign equity, industry (16 dummies), region, and time dummies. Omitted case is a qualified professional, in an elementary occupation working in a limited liability firm. The sample for the fixed effects wage regression covers each company's history since 1996 up to the year before hiring a worker belonging to our main sample.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

B. Employment and firm size: probit estimates

We estimate a probit model for the probability of being hired to a small firm (versus being hired to a large firm) to obtain the weights for the duration models. The probit model describes how the attributes and abilities of displaced individuals contribute to finding a job in firm with fewer than 50 workers. Our choice of independent variables follows previous works such as those by Evans and Leighton (1989) and Idson and Feaster (1990).

Results (Table B1) show that less educated workers coming from smaller and non-knowledge-intensive firms have a higher probability of finding a job in a small firm. Women are just as likely as men of finding employment in small firms, and age positively contributes (with diminishing returns) to employment in small firms. Time to find a job since displacement decreases the probability of being employed in a small firm. The discussion of this particular effect is out of the scope of our paper but deserves further exploration (with a more complete model). Hiring practices of each kind of firm in conjunction with the worker's specific attributes (e.g., prone to more precarious job relationships) might drive this result.

Table B1: Marginal effects for probability of starting job in a firm with fewer than 50 employees

College	-0.092***
	(0.003)
Female	0.002
	(0.002)
Age	0.004***
	(0.000)
Non-employment (one year)	-0.024***
	(0.002)
Non-employment (two years)	-0.034***
	(0.003)
Previous firm was ≥ 50 employees	-0.393***
	(0.003)
Previous firm was knowledge-intensive	-0.078***
	(0.003)
Number of observations	210,620
Wald χ^2 (24)	28,961.6
Prob > χ^2	0.000
Log pseudolikelihood	-123,227.9

Notes: Standard errors in parentheses. Marginal effects (from probit model) calculated for observed values of other variables and averaged over whole sample. Age is quadratic in probit model. Regression also includes controls for year fixed effects.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

C. Regression tables

Table C1: Average marginal effects of college education and high-skilled job on the hazard of job separation: Models with interactions with knowledge intensity and size category

	Education	Skill level	Education and skill level
In firm with fewer than 50 employees			
College in less-knowledge-intensive	-0.043***		-0.012***
	(0.003)		(0.003)
College in knowledge-intensive	0.015***		0.015***
	(0.003)		(0.004)
High-skilled job in less-knowledge-intensive		-0.071***	-0.068***
		(0.002)	(0.003)
High-skilled job in knowledge-intensive		0.004	-0.004
		(0.003)	(0.004)
In firm with 50 employees or more			
College in less-knowledge-intensive	-0.039***		-0.022***
	(0.003)		(0.003)
College in knowledge-intensive	-0.091***		-0.005
	(0.003)		(0.003)
High-skilled job in less-knowledge-intensive		-0.059***	-0.049***
		(0.003)	(0.004)
High-skilled job in knowledge-intensive		-0.163***	-0.161***
		(0.003)	(0.003)
Log of Normal Variance (log σ^2)	-0.508***	-0.382***	-0.374***
	(0.055)	(0.052)	(0.052)
Number of observations	542,891	542,891	542,891
Number of workers	210,620	210,620	210,620
Log likelihood	-510,910.7	-509,282.5	-509,248.9
Log likelihood for model with $\sigma^2 = 0$	-511,316.8	-509,770.1	-509,741.3
p-value for LR test of $\sigma^2/(1+\sigma^2) = 0$	0.000	0.000	0.000

Notes: Standard errors in parentheses. Sample composed of previously displaced workers. Model is a cloglog with unobserved heterogeneity following a Normal distribution with variance σ^2, weighted by the inverse probability of being employed in a small firm. Regressions include the full set of interactions between the relevant human capital variables, size category and knowledge intensity, and controls for worker's tenure, gender, age at entry and its square, dummy for part-time, previous experience in knowledge-intensive firms, and size category of previous job, indicator for industry change, indicator for fixed-term contract, firm's legal structure, log number of establishments, log company's age at entry, region, indicator for manufacturing firms, and firm fixed-effects from wage regression, yearly GDP growth rate (and an interaction with knowledge intensity indicator) and regional unemployment rate. Marginal effects are relative to a worker without college education and/or not in a high-skill job, calculated at observed values of other variables, with respect to the random effect.

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

Table C2: Average marginal effects of tenure on the hazard of job separation:
Model with interactions with knowledge intensity and size category

	Less Knowledge Intensive	Knowledge Intensive
In firm with fewer than 50 employees		
Tenure = 2	-0.052***	-0.049***
	(0.003)	(0.005)
Tenure = 3	-0.080***	-0.060***
	(0.004)	(0.006)
Tenure = 4	-0.089***	-0.102***
	(0.005)	(0.007)
Tenure ≥ 5	-0.108***	-0.105***
	(0.006)	(0.007)
In firm with 50 employees or more		
Tenure = 2	-0.055***	-0.061***
	(0.004)	(0.004)
Tenure = 3	-0.091***	-0.107***
	(0.005)	(0.006)
Tenure = 4	-0.090***	-0.136***
	(0.006)	(0.007)
Tenure ≥ 5	-0.068***	-0.192***
	(0.007)	(0.007)
Log of Normal Variance (log σ^2)	-0.386***	
	(0.053)	
Number of observations	542,891	
Number of workers	210,620	
Log likelihood	-509,655.3	
Log likelihood for model with $\sigma^2 = 0$	-510,115.6	
p-value for LR test of $\sigma^2/(1+\sigma^2) = 0$	0.000	

Notes: Standard errors in parentheses. Sample composed of previously displaced workers. Model is a cloglog with unobserved heterogeneity following a Normal distribution with variance σ2, weighted by the inverse probability of being employed in a small firm. Regression includes the full set of interactions between tenure, size category and knowledge intensity, and controls for worker's education, skill level, gender, age at entry and its square, dummy for part-time, previous experience in knowledge-intensive firms, and size category of previous job, indicator for industry change, indicator for fixed-term contract, firm's legal structure, log number of establishments, log company's age at entry, region, indicator for manufacturing firms, and firm fixed-effects from wage regression, yearly GDP growth rate (and an interaction with knowledge intensity indicator) and regional unemployment rate. Marginal effects are relative to the 1st year of tenure, calculated at observed values of other variables, with respect to the random effect.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table C3: Average marginal effects of firm fixed effects quartile on the hazard of job separation: Model with interactions with knowledge intensity and size category

	Less Knowledge Intensive	Knowledge Intensive
In firm with fewer than 50 employees		
Marginal effect of 2nd quartile of firm fixed effect	-0.013***	-0.032***
	(0.003)	(0.006)
Marginal effect of 3rd quartile of firm fixed effect	-0.030***	-0.045***
	(0.003)	(0.006)
Marginal effect of 4th quartile of firm fixed effect	-0.053***	-0.041***
	(0.004)	(0.007)
In firm with 50 employees or more		
Marginal effect of 2nd quartile of firm fixed effect	-0.054***	-0.024***
	(0.004)	(0.006)
Marginal effect of 3rd quartile of firm fixed effect	-0.061***	-0.061***
	(0.004)	(0.006)
Marginal effect of 4th quartile of firm fixed effect	-0.127***	-0.196***
	(0.004)	(0.006)
Log of Normal Variance (log σ^2)	-0.357***	
	(0.052)	
Number of observations	542,891	
Number of workers	210,620	
Log likelihood	-509,199.6	
Log likelihood for model with $\sigma^2 = 0$	-509,701.5	
p-value for LR test of $\sigma^2/(1+\sigma^2) = 0$	0.000	

Notes: Standard errors in parentheses. Sample composed of previously displaced workers. Model is a cloglog with unobserved heterogeneity following a Normal distribution with variance σ^2, weighted by the inverse probability of being employed in a small firm. Regression includes the full set of interactions between tenure, size category and knowledge intensity, and controls for worker's education, skill level, gender, age at entry and its square, dummy for part-time, previous experience in knowledge-intensive firms, and size category of previous job, indicator for industry change, indicator for fixed-term contract, firm's legal structure, log number of establishments, log company's age at entry, region, indicator for manufacturing firms, and firm fixed-effects from wage regression, yearly GDP growth rate (and an interaction with knowledge intensity indicator) and regional unemployment rate. Marginal effects are relative to the 1st quartile, calculated at observed values of other variables, with respect to the random effect.

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