INTER-FIRM MOBILITY AND WAGES IN THE ITALIAN ICT INDUSTRY

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Preliminary version – 7 September 2012

Abstract – This paper assesses the extent of inter-firm transferability of the skills developed by employees in the Italian ICT industry between 1990 and 2004. Skill transferability is measured through the wage premium recognised to firm changers compared to firm stayers and is appraised through a semi-parametric difference-in-differences approach with propensity score matching, Based on WHIP, a longitudinal dataset of employer-employee matched data representative of the Italian labour market, the results of the empirical analysis support the hypothesis of inter-firm transferability of skills. No significant differences in wage growth were detected between firm stayers and firm changers. However, the lower wage growth experienced by firm switchers who move outside the ICT industry compared to firm switchers to a close industry point out the existence of limits to inter-industry skill transfer.

Keywords: job mobility; skills; wage; ICT; empirical analysis

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1. Introduction

Shorter duration and higher volatility characterise an increasing share of employment relationships in industrialised countries. Skill transferability and return to employer mobility thus represent crucial requirements for the good functioning of labour markets, as witnessed by the growing amount of studies on this topic (Kletzer, 1996; Parent, 2000; Zangelidis, 2008; RPIC-ViP, 2011). Workers with low skill transferability risk longer unemployment spells between jobs and face higher probability of poorer working conditions when returning to employment (Neal, 1995). Those risks are particularly strong when involved professional skills concern fast changing technologies and processes, due to the higher rates of skill obsolescence (De Grip and Van Loo, 2002).

All the above concerns are emphasised in the case of professionals in the area of Information and Communication Technologies (ICTs). The processes of liberalisation and re-regulation that invested the telecommunication sector in the 1990s and the technology-driven diffusion of Internet-based services sustained the growth of the whole ICT industry (Slaughter *et al.*, 2007; Solimene, 2008) and promoted skill restructuring and inter-firm mobility among employees (Garrone and Sgobbi, 2001). In addition, the pervasive diffusion of ICTs across all economic and non-economic activities seemingly provides additional employment opportunities outside the borders of the ICT industry. Skill transferability thus represents a crucial requirement for ICT employees and the costs and benefits of employer change deserve in-depth investigation.

The empirical analysis provided in this paper tests the borders of skill transferability by assessing the return to employer mobility for firm changers in the same industry and firm changers moving outside the ICT industry compared to firm stayers. The underlying hypothesis is that a wage loss for firm and industry switchers signals that the value attached by a new employer to a bundle of skills developed in the ICT sector is lower than the value recognised by the initial employer. In contrast, a wage premium or the lack of a significant wage differential signal the transferability of the skills provided by employer switchers.

The empirical analysis is based on the 1990-2004 section of WHIP, a longitudinal dataset including a representative sample of employment relationships in Italy. By applying a semi-parametric difference-in-differences approach with propensity score matching, the paper shows that ICT employees moving to a new employer neither benefit from a wage premium nor suffer from a wage penalty compared to firms stayers.

However, the lower wage growth experienced by firm switchers who move outside the ICT industry compared to firm switchers to a close industry point out the existence of limits to inter-industry skill transfer.

The rest of the paper is organised as follows. The next session outlines the drivers that make skill transferability a critical requirement for ICT workers and briefly surveys the literature on the return to industry-specific skills. Section 3 illustrates the empirical strategy used for comparing wage growth across different types of ICT employees, whereas Section 4 presents the data used in the empirical analysis. Section 5 reports the empirical results and the last section provides some concluding remarks.

2. Skill transferability and ICT workers

Several studies point out the crucial role played by human resources in the development of an information society and the harms potentially associated with skill shortage and skill gap[1] among ICT professionals both in the ICT industry and in other economy sectors (Forth and Mason, 2004; Wintjes and Dunnewijk, 2008; Didero *et al.*, 2009; Colomo-Palacios *et al.*, 2012). The risk of mismatch between demand and supply of ICT skills is deeply connected with the intertwined key events that have marked the history of information and communication technologies since the 1980s (OECD, 2005; Solimene, 2008; Didero *et al.*, 2009). First, by unifying elaboration tools and transport and delivery channels for different types of information (voice, data, images), digitalisation processes drove the merge between telecommunications, computer industry and production of digital contents. Second, the switch of traditional ICT manufacturers from capital-intensive good production to knowledge-intensive service delivery has been driving progressive processes of outsourcing and offshoring, at least in industrialised countries (OECD, 2005; Didero *et al.*, 2009; García-Crespo *et al.*, 2010; OECD, 2011). Third, the pervasiveness of ICT made basic ICT-skills a requirement to perform a large range of working and non-working tasks in the daily life of most citizens and opened new positions for ICT professionals in virtually all economic activities (European Commission, 2012).

The consequences of the above mentioned drivers of change for ICT workers are not negligible. Professional profiles in the field of ICTs are characterised by the continuous evolution (and sometimes revolution) of related skills and tasks (Casado-Lumbreras *et al.*, 2011; Trigo *et al.*, 2010). In addition, the uncertainty of professional careers and the offshoring of ICT manufacturing and services has discouraged the en-

[1] Skill shortage refers to the difficulty met by employers in filling up vacant positions due to the lack of suitably skilled candidates, whereas skill gap concerns the mismatch between the skills required to occupy a position within an organisation and the skills provided by the employee in that role.

rolment in ICT-targeted academic curricula in recent years (European Commission, 2012) leading to a so-called war for talent (Colomo-Palacios *et al.*, 2010). These features reflect in the difficulty of designing and tracking career paths for ICT professionals, as well as in their heterogeneous background (Sherry *et al.*, 2012). Within such a framework, skill transferability becomes not only a means in support of a comprehensive target such as the growth of an information society, but also a basic requirement to ensure employability and improve the employment opportunities of the involved workers (Quan *et al.*, 2011).

Economic and organisation studies have long classified employee skills according to the dichotomy between general skills and specific skills (Becker, 1975). Whereas general skills provide value added to several employers, specific skills are hardly transferable outside the workplace where they developed. Despite the popularity of those concepts, agreement has progressively emerged on their inability to account for the whole range of skills traded in labour markets[2]. Among the early supporters of skills as a continuum between the opposite extremes of general and specific skills, Stevens (1996) defines transferable skills as an intermediate category whose applicability, despite restricted to a limited cluster of employers, spans beyond the borders of the firm.

Due to the policy concerns raised by unemployment, most of the existing studies on skill transferability focus on the wage loss suffered by displaced employees when returning to employment (see, e.g., Neal, 1995; Parent, 2000). Several studies support the significance of industry-specific effects[3] (Kletzer, 1996; Parent, 2000; Weinberg, 2001) and, in the case of the ICT industry, Ong and Mar (1992) report that employees displaced from Silicon Valley manufacturing firms suffered no wage losses when finding a new job within the same industry or at other high-tech companies, contrary to employees who moved to non-high-tech firms.

However, the large majority of the studies on skill transferability across firms and industries focus on the return to experience and skills developed in the current job and disregard how the different characteristics of the origin and the destination industries may constrain the transferability of an employee skills and impact on her or his

[2] The notion of transferable skills has met particular success in management studies, where the concept of "boundaryless career" across different occupations and employers has been opposed to "traditional" careers within the borders of a single organisation (Inkson *et al.*, 2012).

[3] The acknowledgement of the role played by industry-specific skills triggered additional studies focused on the return to occupation-specific skills (Poletaev and Robinson, 2008; Zangelidis, 2008; Kambourov and Manovskii, 2009; Sullivan, 2010) and task-specific skills (Gathmann and Schönberg, 2007). These recent developments suggest that, when accounting for occupation- or task-specific skills, the returns to firm and industry tenure suffer a significant downsize. In addition, inter-firm skill transferability varies across occupations (Poletaev and Robinson, 2008) and accumulated skills shape career paths and individual career choices (Gathmann and Schönberg, 2007).

wage. Kletzer (1996) argues that a simple dichotomous contrast between industry stayers and industry switchers does not offer a complete picture of skill transferability among industries. Despite some researchers provide evidence about the higher returns associated with moves to closer industries (Ong and Mar, 1992; Kletzer, 1996; Pack and Paxson, 1999; Poschl and Foster, 2010), systematic research on inter-industry distance and its impact on the wage of industry switchers is still missing.

3. Empirical strategy

The return to skill transferability across different firms and different industries is usually tested by estimating the relationship between job mobility and wage mobility. For instance, Parent (2000) assesses the return to tenure with the current employee and experience in the current industry, whereas Neal (1995) provides separate estimates of the return to pre-displacement tenure for displaced employees who either found a new job in their original industry or moved to a different sector. Those approaches provide evidence on the benefits of accumulating firm-specific skills (Neal, 1995) and industry-specific skills (Parent, 2000) when remaining in the same sector. However, they do not allow assessing the borders of skill transferability i.e., how far an employee can move from the original workplace before her or his skills loose value for potential employers.

A simple model for testing the limits of skill transferability is reported in equation (1), where ω_{it} is the wage received by employee i at time t, $\overline{M_{it}} = \{M_{1,it}, M_{2,it}, \ldots, M_{H,it}\}$ is a vector of H binary variables accounting for recent employer and industry change, $\overline{Z}_{it}$ is a vector of control variables and ε_{it} is an error term.

$$\ln \omega_{it} = \beta_0 + \overline{M_{it}}\,\overline{\beta_1} + \overline{Z}_{it}\,\overline{\beta_2} + \varepsilon_{it} \qquad (1)$$

A significant and positive (negative) coefficient for a generic move $M_{h,it}$ signals a wage premium (wage loss) for movers to a new employer in industry h compared to the reference category of firm stayers, whereas a non-significant coefficient reflects the lack of statistical differences between movers and stayers.

Nevertheless, the estimate of equation (1) presents substantial empirical challenges. First, the choice of moving to a different employer and, possibly, to a different industry is endogenous with wage after change (Kletzer, 1996). The active search for a better employer-employee match or the deterioration of individual productivity in the new workplace may explain both job mobility and earnings in the new job. Instrumental variables are often used to overcome the potential biases due to the presence of endogenous explanatory variables (see, e.g., Parent, 2000).

However, the identification of suitable instruments for all the distinct binary variables that account for moves to new employers and new industries in equation (1) looks particularly challenging. Propensity Score Matching (PSM) provides an alternative approach to identify the average impact of job mobility for firm changers compared to firm stayers. The core idea of PSM, originally developed to assess the causal effects of policy measures in natural experiments[4], is that comparison between treated and control group should be based on individuals as similar as possible along a set of pre-treatment characteristics X affecting both the observed outcome and the probability of selecting into the treatment. A matching mechanism rules out systematic differences between treated and untreated individuals and allows for an unbiased estimate of the average treatment on the treated. Matching algorithms are based on a balancing score b(X) i.e., a function of the pre-treatment observable variables X such that the conditional distribution of X given b(X) is the same for treated and control individuals (Conditional Independence Assumption). The computational difficulty of matching similar individuals increases with the dimension of vector X. However, Rosenbaum and Rubin (1983) proved that conditional independence is still valid if controlling for the propensity score i.e., the probability of participation based on the X covariates, instead on vector X. Lechner (2001) extends Rosenbaum and Rubin's findings to the case of multi-level treatments and proposes a four-step procedure for a matching estimator of treatment effects. An empirical implementation of the suggested estimator is provided by Larsson (2003) in the case of active labour market programmes for young Swedish workers[5].

Despite providing an appealing answer to the problem of assessing the impact of an endogenous employer change on wage, PSM suffers from significant limitations. The conditional independence assumption requires the probability of participation to be captured by pre-treatment observable variables X, a condition hardly met in case of unobservable individual heterogeneity. In addition, PSM does not account for possible time trends unrelated with the treatment. When information on output and covariates is available for treated individuals and for the control groups both before and after the former are exposed to the treatment, those problems can be solved by a difference-in-differences (DID) approach. In DID estimates the average gain in output for the treated after and before the treatment is compared to the average gain enjoyed by the control group in the same time period. The double differentiation – across groups and across time – accounts for both unobserved time-invariant differences between treated and un-

[4] For recent surveys, see Caliendo and Kopeinig (2008) and Imbens and Wooldridge (2009).

[5] Additional examples are provided by Dorsett (2006), who assesses the impact of four programmes of subsidised fixed-term employment and training promoted by the UK government on the probability of job entry and by Davia (2010), who measures the wage impact of different types of job mobility in the early career of Spanish workers.

treated individuals and for time trends independent of the considered treatment (Imbens and Wooldridge, 2009).

Nevertheless, also the applicability of DID estimators is limited by strong constraints. DID estimators assume that in the lack of exposure to the treatment the average outcome of treated individuals would have followed the same time trend observed for the control group, irrespective of possible unbalance in the distribution of pre-treatment characteristics affecting the output of treated and untreated individuals (Abadie, 2005). The combination of propensity score matching with difference-in-differences methods (PSM-DID) consequently provides a promising solution to account for both unobserved heterogeneity, treatment-independent time trends and unbalanced distribution of pre-treatment characteristics associated with the observed outcome among individuals in treated and control groups (Heckman *et al.*, 1997; Blundell and Costa Dias, 2000; Imbens and Wooldridge, 2009). The recent surge of empirical applications of PSM-DID estimators in the areas of labour and education economics confirms the potentiality of those tools to solve problems of selection on observables and independent time trends[6]. However, with the notable exception of Davia (2010), the existing contributions focus on binary treatments and neglect multi-level treatments.

A semi-parametric estimator for testing the average treatment on the treated in case of multi-level treatment is provided by Abadie (2005). Consider a multi-level treatment consisting in H mutually exclusive levels and a two time periods set. No individual is exposed to any treatment in the first period, whereas the unconditional probability of being exposed to treatment h in the second period is equal to P(H=h). For each treatment level, $Y_t(1)$ represents the outcome observed for individuals exposed to that treatment at time t, while $Y_t(0)$ is the counterfactual outcome. As no individual is treated in the first time period, $Y_0(0)=Y_0(1)$ $\forall h \in H$. Under the conditional independence assumption

$$E[Y_1(0) - Y_0(0)|X, H] = E[Y_1(0) - Y_0(0)|X] \qquad (2)$$

and the overlap assumption that the support of the propensity score for the treated is a subset of the propensity score for the untreated, Abadie (2005) shows that the average treatment on the treated for treatment level h compared to the counterfactual of untreated individuals can be modelled as

$$\tau_{ATT} = E\left\{\frac{(Y_1 - Y_0)}{P(H=h)} * \left(h - h_0 * \frac{P(H=h|X)}{1 - \sum_{j \in H} P(H=j|X)}\right)\right\} \qquad (3)$$

In equation (4), Y_1 and Y_0 are the outcomes observed for the same individual in two subsequent time periods; h is a binary variable equal to 1 if the observed individual is exposed to treatment at level h; h_0 is a binary variable equal to 1 if the observed indi-

[6] See, e.g., Blundell *et al.* (2004), Bergemann *et al.* (2009), Leombruni *et al.* (2010), Buscha *et al.* (2012).

vidual is exposed to no treatment; $P(H = h|X)$ is the individual propensity score for treatment level h given a set of X covariates; and $1 - \sum_{j \in H} P(H = j|X)$ is the individual propensity score for no treatment.

A consistent and $\sqrt{N}$-asymptotically normal estimator of the average treatment on the treated for treatment level h can be consequently calculated as in (4)

$$\hat{\tau}_{ATT} = \frac{1}{N} \sum_{k=1}^{N} \left\{ \frac{(Y_1 - Y_0)}{P(H=h)} * \left(h - h_0 * \frac{\hat{P}(H=h|X)}{1 - \sum_{j \in H} \hat{P}(H=j|X)} \right) \right\} \quad (4)$$

where N is the number of individuals either in treatment level h or in no treatment. It has to be noted that if the participants in two treatments differ in a non-random fashion, the average treatment on the treated will not be symmetric (Lechner, 2001) and $\hat{\tau}_{ATT,h_i h_j} \neq \hat{\tau}_{ATT,h_j h_i} \; \forall \, h_i, h_j \in H$.

In case of binary treatment, the estimator in (5) can be re-written as

$$\hat{\tau}_{ATT} = \frac{1}{N} \sum_{k=1}^{N} \left\{ \frac{(Y_1 - Y_0)}{P(D=1)} * \frac{D - \hat{P}(D=1|X)}{1 - \hat{P}(D=1|X)} \right\} \quad (5)$$

where D is equal to 1 for individuals exposed to treatment.

The estimator proposed by Abadie (2005) presents important advantages over other PSM-DID estimators (e.g., Heckman *et al.*, 1997; Blundell and Costa Dias, 2000). As the distribution of covariates is balanced between treated and untreated by simply weighting untreated observations through their covariate-based propensity scores, Abadie's parsimonious estimator requires no additional hypothesis on the matching mechanism. In addition, the extension to the multi-level case makes this estimator suitable for testing the wage effect of moving to a different employers and possibly different industries compared to a counterfactual sample of firm stayers.

4. Data

The analysis of the return to inter-firm skill transferability is based on WHIP (Work Histories Italian Panel), a random sample of the archives of the Italian Institute for Social Security (INPS) that records the compulsory social allowances paid by employers for their employees[7]. WHIP provides a dynamic panel including about 862,000 employment relationships held by about 350,000 individuals between 1985 and 2004. Information on employers concerns geographical location, sector of economic activity, annual average number of employees and firm age. Data on employees include age, sex and region of birth. For each employment relationship, identified by a unique code, WHIP provides information about start date, end date, gross reward per year, equivalent

[7] WHIP samples the INPS archive by extracting the records on employees born either on March 10th, June 10th, September 10th or December 10th of each year. For a detailed description of WHIP see Leombruni *et al.* (2010).

worked days per year, occupation, collective labour agreement in force, job level and administrative events that each year may affect an employment relationship, such as maternity leave or illness leave.

Administrative data such as WHIP are based on objective measures and their reliability is cross-checked by all interested actors, including employers, employees and public officers. They thus provide a more reliable source of information compared to survey data, as the latter are affected to a larger extent by subjective evaluation and measurement error.

To assess the return to mobility firm change can be framed as a treatment, whereas firm stayers provide a control group. The move to a different firm corresponds to a multi-level treatment, as an employee could sign a new contract with another banking firm or could move to a different industry. To test the borders of skill transferability from the ICT industry I will assess the relative wage premium (or wage loss) of firm movers who find a new job in industries progressively more distant from their source industry. The underling hypothesis is that highly firm-specific skills have no value outside the workplace where they developed and no external employer is expected to pay for them. On the contrary, fully transferable general skills are expected to be rewarded by any employer outside the source firm. In case of partial skill transferability, we expect positive returns when the old and the new employer make use of similar tools, techniques and procedures. The larger the distance between source and destination employer, the higher the share of lost skills and consequently the lower the return to transferable skills.

Measuring the distance between destination industries and the banking sector is crucial for testing our research hypothesis. Depending on the nature of the available data, past studies resorted either to industry classification codes (Ong and Mar, 1992; Kletzer, 1996; Parent, 2000) or to occupation classification codes (OECD, 2004; Didero *et al.*, 2009). In both cases, the disaggregation level of the chosen classification variable crucially affects the quality of the research outputs. To protect the privacy of employers and employees, WHIP provides information on industries and occupations at a rather aggregate level. Industry codes are available at the 1-digit or, in some cases, 2-digit level, whereas occupation codes are available at the 1-digit code. Nevertheless, the availability of information on the national collective labour agreement allows identifying employees in the Italian ICT industry with a reasonable degree of accuracy. Unfortunately, the 3-digit classification of national collective labour agreements changed between 1989 and 1990, with no biunique correspondence between old and new codes. Also due to censored observation of tenure before 1985, the empirical analysis is thus restricted to the period 1990-2004.

The labour agreements of employees at public telecommunication operators and at data management service providers are identified by specific 3-digit codes. In contrast, ICT employees at manufacturers of telecommunication equipment and providers of installation services are identified by crossing the 1-digit industry code for transport, storage and telecommunications with four 3-digit labour agreement codes for manufacturing and installation services. WHIP classifies computer programming, information service activities other than data management and IT hardware manufacturing under the wide 1-digit industry code of "Real estate activities, information technologies, R&D and other service activities". ICT employers and employees in this sector are identified by crossing the 1-digit industry code with four 3-digit labour agreement codes for manufacturing and installation services.

The unit of analysis to study the return to firm and industry mobility for ICT employees industry is provided by workers who are employed in the ICT industry at the end of a generic year t0 between 1990 and 2002 and who are still in employment 2 years later. Employees who remain with the same employer between the end of time period t0 and the end of time period t1 are labelled as stayers. On the contrary, employees who move to a different firm are identified as firm switchers. Among the latter, industry switchers are those firm changers who move to an employer outside the ICT industry.

In order to avoid an over-representation of firm-stayers, the database includes for all employees the most recent observation between 1990-1992 and 2002-2004. However, wage dynamics is significantly affected by the phase of the working life cycle. Career opportunities decrease with age due to the lower number of available positions at higher hierarchical levels and to decelerated learning processes, possibly coupled with skill obsolescence. In addition, higher mobility costs and shorter time horizons to cushion those costs reduce the propensity to firm change by older employees. The choice to select the most recent observation of ICT employees between 1990-1992 and 2002-2004 may consequently generate an over-representation of elderly employees characterised by slower wage dynamics. To avoid possible biases due to the approaching of the retirement from the labour market, we discarded observations concerning individuals above 55 years of age. In addition, we removed observations on 1% top and bottom earners by 1-digit occupation observations concerning multiple employment relationships starting or ending on the same date, employees with temporary contracts and employees in managerial jobs[8] and observations with missing information on wage,

[8] Observations on temporary contracts are deleted due to the difficulty of discriminating between voluntary and involuntary firm mobility. Observations on managerial jobs were not included in the empirical analysis because collective labour agreements for managerial positions in Italy are mostly non-industry-

working hours or job. The resulting database includes 2,362 observations, 483 of them concerning firm changers.

Table 1 reports some statistical information on the examined sample. Probably due to the inclusion of former monopolistic public telecommunication operators, the average age of sampled employees is higher than the figures usually reported by the international literature for the ICT industry (Didero *et al.*, 2009). The close numbers calculated for firm, occupation, job and industry experience suggest that most ICT employees develop their career within a single employer and that the initial choice after leaving the education system has a strong impact on the subsequent development of professional paths. This intuition is supported by the figures on employer and industry mobility. Employer change involves 20.4% of observations and about half of these moves concern industry changes.

Tables 2 and 3 provide some preliminary evidence on wage premium and wage losses associated with different types of employment mobility. Table 2 shows that, on average, the wage of firm switchers in their former job is significantly lower than the wage of firm stayers. Despite the more substantial wage increase they benefit from when moving to a different employer, their wages in the second time period still lag behind those of firm stayers. Table 3 provides separate comparisons for the wage levels and the wage increase of firm switchers by destination industry. Despite not accounting for possible structural differences in the distribution of characteristics that affect both the decision to move to another employer and wage levels and differentials, the figures in Table 3 support the intuition that firm changers are a rather heterogeneous group and that a comparison limited to firm stayers and firm changers may hamper the identification of more articulated dynamics. If employees who move to other ICT firms manage to catch up with firm stayers thanks to sizable average wage growth, gains are smaller when ICT workers move to less closely related industries. This preliminary evidence supports the hypothesis of declining returns to skills for employees who leave their original industry and justifies the implementation of more sophisticated tools of analysis.

5. Empirical analysis

Following Abadie (2005), the empirical analysis to test the return to firm and industry mobility from the Italian ICT industry develops along two steps. The first step concerns the calculation of the propensity score to select into firm mobility. The second step involves the estimation of the average wage increase for mobile employees compared with a counterfactual of firm stayers. Both steps are replicated in case of binary treat-

specific. Consequently, contract codes for labour agreements do not always allow for the identification of a manager's industry.

ment, where firm changers are compared with firm stayers irrespective of their destination industry, and in case of multi-level treatment, where the analysis is detailed for movers to other banking firms, movers to the finance industry and movers outside the finance industry.

Table 1. ICT employees in WHIP – Descriptive statistics 1990-2004

		Min	Max	μ	σ
Age [years]		18	55.000	37.415	9.988
Job experience [years]		0	18.960	7.690	5.048
Industry experience [years]		0	18.960	7.019	5.160
Occupation experience [years]		0	18.960	8.469	5.039
Firm tenure [years]		0	16.830	6.903	5.183
Unemployment before current position [years]		0	18.960	0.301	1.062
Firm size [employees]		1	94,858	45,170.350	41,234.143
		%			
Gender	Female employees	0.300			
Occupation	Blue collars	0.242			
	White collars	0.740			
	Middle managers	0.018			
Birth area	North-West Italy	0.284			
	North-East Italy	0.126			
	Centre Italy	0.240			
	South Italy	0.320			
	Foreign country	0.031			
Inter-firm mobility	Firm switchers	0.204			
	Industry switchers	0.100			

Source: Elaboration from WHIP; 2,362 observations

Table 2. Wage differentials between firm stayers and firm switchers

	Firm switcher	N	μ	σ	Std. Error Mean	t-test for equality of means t	df	
Gross hourly wage in t0	No	1,865	8.219	2.442	0.057	7.798	649.561	***
	Yes	477	7.069	2.972	0.136			
Gross hourly wage in t1	No	1,865	8.427	3.427	0.079	3.138	687.221	***
	Yes	477	7.827	3.798	0.174			
Δ total hourly wage between t0 and t1	No	1,865	0.209	2.602	0.060	-4.355	781.640	***
	Yes	477	0.758	2.420	0.111			

*Equal variances not assumed; deflated wages (€, base=1992); *** p< 0.01*

Table 3. Wage differentials by destination industry

	Gross hourly wage in t0			Gross hourly wage in t1			Δ gross hourly wage		
ANOVA F-test	51.894	***		18.537	***		10.366	***	
Games-Howell test for multiple comparisons	Mean difference	Std. Error		Mean difference	Std. Error		Mean difference	Std. Error	
Movers to ICT vs. Firm stayers	-0.560	0.203	**	0.200	0.266		0.760	0.174	***
Movers outside ICT vs. Firm stayers	-1.755	0.190	***	-1.423	0.238	***	0.333	0.160	*
Movers outside ICT vs. Movers to ICT	-1.196	0.266	***	-1.623	0.339	***	-0.427	0.221	

*Deflated gross hourly wages (€, base=1992); *** p< 0.01 ** p< 0.05 * p< 0.10*

Table 4. The drivers of propensity to firm change

	β	Std. error	
Constant	4.803	0.645	***
Tenure t0	-0.260	0.051	***
Squared tenure t0	0.015	0.003	***
Age t0	-0.061	0.010	***
Gender[(a)]	-0.380	0.158	**
Part time t0	0.106	0.221	
Blue collar t0[(b)]	-1.017	0.456	**
White collar t0[(b)]	-1.014	0.426	**
Ln Dwage peers t0	0.275	0.269	
Ln firm size t0	-0.223	0.031	***
Telecommunications t0	-0.700	0.163	***
North East t0[(c)]	-0.156	0.180	
Centre t0[(c)]	0.005	0.172	
South t0[(c)]	-1.017	0.238	***
-2 Log likelihood	1,450.735		
Nagelkerke R Square	0.502		

*Dependent variable: Firm leaver; binary logistic regression; 2,362 observations; *** p< 0.01 ** p< 0.05 * p< 0.10*

Regression includes 12 binary controls for two-year periods

(a) Reference category: male employees. (b)Reference category: Middle managers.

(c) Reference category: works in North West Italy in t0.

Propensity score matching provides reliable results as long as the balancing score b(X) actually captures the probability of participation into a treatment. The rich set of pre-treatment observable covariates X provided by WHIP enhances the chances of controlling for the factors affecting the probability of receiving a treatment and achieving the observed outcome. The coefficients of the binary logistic model used to calculate the propensity score to participate in the binary treatment of moving to a new employer are reported in Table 4. The model displays a satisfactory prediction power, with 85.9% of cases correctly classified and a Nagelkerke R-Square of 0.502.

All coefficients are in line with the results from the past literature. Inter-firm mobility decreases with tenure, age, firm size and opportunities in the local labour market (lower propensity to employer change in Southern Italy). Female employees display lower mobility compared to their male colleagues and the propensity to move to a new firm is significantly higher among employees with higher hierarchical positions. An additional covariate is based on the evidence that workers are sensitive to their income rank in a group of peers (Boyce *et al.*, 2010). The dissatisfaction generated by a lower income compared to other employees in a similar job could trigger search processes aimed at improving the individual perception of income rank. A proxy for relative income is calculated as the difference in logwage in the first time period and the average logwage of other employees in the same job grade and labour agreement[9] (Ln dwage peers in Table 4). However, higher wage differentials with peers in the same job do not significantly increase the probability to select into firm mobility. On the contrary, working in the telecommunication sector, traditionally the segment of the ICT industry characterised by best working conditions, is significantly associated with lower firm mobility. Eventually, the binary logistic regression controls for fixed effects due to each two-year period considered (from 1990-1992 to 2002-2004). Two-year period controls and are jointly significant determinants of the probability to select into a binary treatment.

The propensity score for multi-level treatment is calculated through a multinomial logistic regression where the reference category is represented by firm stayers as opposed to moving to another ICT firm and moving outside the ICT industry (Table 5). Compared to the binomial regression, the multinomial analysis includes an additional pre-treatment variable aimed at discriminating among the different destinations of firm switchers. This variable accounts for the relative attractiveness of the destination industry compared to the source one. Attractiveness is calculated as the employment growth rate in the destination industry between t0 and t1. The significance displayed by those coefficients in the multinomial model confirm the importance of employment growth at the industry level as a predictor of the destination industry (Kletzer, 1996).

Also the multinomial logistic regression explains a high share of variance in data (Nagelkerke pseudo R-Square is equal to 0.466) and provides a satisfactory classification power (Table 6). The percentage of correctly classified cases ranges from 96.1% for firm stayers, to 24.7% for movers to other ICT firms, to 29.6% for movers outside the ICT industry[10].

[9] I verified that at least 20 observations were recorded in WHIP for each labour agreement/job grade cell.

[10] Those figures are much higher than those related, for instance, by Larsson (2003), who reports correct classification rates between 6.8% and 76.1%.

Table 5. The drivers of propensity to firm and industry change

	Move to ICT			Move outside ICT		
	β	Std. Error		β	Std. Error	
Constant	4,998	4,367		6,379	4,198	
Tenure t0	-0,280	0,062	***	-0,234	0,067	***
Squared tenure t0	0,017	0,004	***	0,012	0,005	**
Age t0	-0,050	0,012	***	-0,071	0,012	***
Gender[(a)]	-0,662	0,199	***	-0,138	0,194	
Part time t0	-0,088	0,295		0,198	0,256	
Blue collar t0[(b)]	-1,325	0,502	***	-0,549	0,621	
White collar t0[(b)]	-1,040	0,460	**	-0,753	0,589	
Ln Dwage peers t0	-0,528	0,331		0,027	0,330	
Ln firm size t0	0,251	0,039	***	0,192	0,040	***
Telecommunications t0	-0,767	0,203	***	-0,676	0,206	***
North East t0[(c)]	-0,101	0,224		-0,167	0,217	
Centre t0[(c)]	0,154	0,207		-0,179	0,222	
South t0[(c)]	-0,870	0,300	***	-1,118	0,321	***
Sector Attractiveness	-5,932	2,076	***	3,876	2,078	*
-2 Log likelihood	2,031.601					
Nagelkerke R Square	0.466					

*Reference category of the dependent variable: Firm stayer; multinomial logistic regression; 2,362 observations; *** p< 0.01 ** p< 0.05 * p< 0.10*

Regression includes 12 binary controls for two-year periods

(a) Reference category: male employees. (b)Reference category: Middle managers.

(c) Reference category: works in North West Italy in t0.

Table 6. Predictive power of the multinomial logit model

	Predicted			
Observed	Firm stayers	Move to ICT	Move outside ICT	Percent Correct
Firm stayers	1,782	37	36	96.1%
Move to ICT	147	59	33	24.7%
Move outside ICT	127	35	68	29.6%

The multinomial logistic model "breaks up" the category of firm switchers into two distinct sub-groups. The use of this model is thus reliable as far as the assumption of the independence of irrelevant alternatives is respected (Larsson, 2003). The comparison between the coefficients of the multinomial model and the coefficients of three separate binomial regressions restricted to firm stayers and movers to other banking firms, financial firms and other firms, respectively, did not point out dramatic differences. The assumption of the independence of irrelevant alternatives can thus be regarded as valid. In addition, calculated propensity scores meet the overlap assumption, i.e., $0 < P(H = h|X) < 1 \ \forall h \epsilon H$.

The exam of the coefficients of the multinomial regression reveals interesting differences among firm switchers by destination industry. First, the employment growth rate in the destination industry is a powerful driver of the propensity to leave the original employer, yet with opposite effects for industry stayers and industry switchers (see the coefficients of variable Sector Attractiveness in Table 5). A 1% increase in this differential rises by 48% the odds of leaving the ICT industry compared to the odds of remaining with the same employer and lowers by 99% the odds of moving to another ICT firm.

Male employees reveal a higher propensity to move to another ICT firm, whereas gender is not a significant determinant of the decision to leave the ICT industry. In a similar way, ICT firms display a higher propensity to hire middle managers rather than blue or white collars from their competitors, whereas the initial occupation does not significantly impact on the probability to move to a non-ICT employer.

As expectable, higher initial tenure and older age negatively affect the propensity to move to a different firm. Interestingly enough, an initial low ranking in the wage distribution of peers in the same job displays no significant impact on the propensity to change employer (see the coefficients of variable Ln dwage peers in Table 5). On the contrary, initial employment in the TLC segment and location in a Southern region of Italy negatively impact on both the probability to move to another ICT and to leave the ICT sector.

Table 7 reports the difference-in-differences estimates of the return to firm mobility calculated according to formula (5) in section 3 for the binary case and to formula (4) for different options of the multi-level case. All standard errors are bootstrapped with 500 repetitions. The results in Table 7 markedly differ from the output of the ANOVA reported in Table 3 and confirm the need of accounting for observed and unobserved unbalance in the distribution of pre-treatment characteristics affecting the output of treated and untreated individuals.

The first panel of Table 7 shows that, after controlling for pre-treatment differences and for individual unobserved heterogeneity, no significant difference exist in the wage growth experienced by firm switchers and firm stayers. When the average treatment on the treated accounts for the destination industry (second panel of Table 7), only minor changes emerge. Data display no significant differences in wage growth between movers to ICT industry and firm stayers, as well as between movers outside the ICT industry and firm stayers. However, movers outside the ICT industry suffer from a significant penalty compared to firm switchers who remain in the ICT sector.

The results displayed in Table 7 provide substantial support to the hypothesis of skill transferability from the ICT sector. Also when moving to employers in markedly distant sectors, former ICT employees are valued by their new employers and, at least in the short run, their wage dynamics do not display significant differences compared to the option of remaining with the initial employer. At the same time, the declining average advantage perceived by firm switchers with the distance of the destination industry from the ICT sector confirms that the observed employees sell transferable rather than general skills to their new employers. Recruiting from a competitor means saving in formal and informal training for other ICT firms, who are willing to pay a wage differential to attract readily-operative employees. However, the re-usability of skills quickly declines as workers move to industries characterised by more diversified outputs and processes.

Table 7. The return to firm mobility – PDM-DID estimates of wage increase

	Differential total gross hourly wage	Bootstrap std. error	z	
Binary treatment				
Firm switchers vs. Firm stayers	0.114	0.218	0.52	
Multi-level treatment				
Movers to ICT vs. Firm stayers	0.303	0.302	1.01	
Movers outside ICT vs. Firm stayers	-0.840	0.264	-0.32	
Firm stayers vs. Movers to ICT	-0.270	0.298	-0.90	
Movers outside ICT vs. Movers to ICT	-1.954	1.173	-1.67	*
Movers to ICT vs. Movers outside ICT	0.747	0.692	1.08	
Firm stayers vs .Movers outside ICT	1.051	1.261	0.83	

*47,145 observations; *** p< 0.01; Deflated gross hourly wages (€, base=1992)*

5. Concluding remarks

In recent years, higher job volatility, rising training costs and more frequent organisation and technological change have increased the attention of labour market players towards transferable skills. Transferable skills increase workers' employability and provide firms with ready-to-use competences and capabilities to fill up opening and vacant positions. Assuming that transferable skills will be signalled by non-negative wage progression of firm switchers compared to firm stayers, this paper assessed the borders of transferability for the skills developed within a sector traditionally described as a collection of internal labour markets characterised by firm-specific skills, i.e., the ICT industry.

Contrary to the prevailing approach in the literature for apprising the return to inter-industry mobility, this paper claims that the distance between source and destination sectors matters. The larger the difference in technologies, techniques and labour flow organisation between the source and the destination industry, the lower the probability of inter-industry skill transfer. The empirical analysis accounts for the distance between source and destination sector by modelling firm change as a multi-level treatment whose intensity increases with the distance between the banking industry and the sector where firm switchers find a new employment contract. In order to assess the relative wage premium of firm switchers compared to firm stayers accounting for observed and unobserved individual heterogeneity, I implemented a DID-PSM approach for a multi-level treatment.

The outcomes of the econometric estimates support the hypothesis of significant, yet limited transferability for the skills developed by employees in the ICT industry. The lack of significan differences between the wage progression of firm stayers and different categories of firm switchers suggests that the skills developed at ICT employers are appreciated also beyond the industry borders. However, the lower growth experienced by movers outside the ICT industry compared to movers to other ICT firms point out the non-complete transferability of ICT skills. These findings emphasise the need for training programmes and involvement practices aimed at reducing the risk of skill obsolescence in an industry still characterised by high rates of technology and organisation change. Under the perspective of less protected and more competitive labour markets, a cocktail of fast skill obsolescence and limited skill transferability outside the source industry may prelude to the segregation of employees unable to catch up with fast skill change into lower-paying market segments.

Acknowledgements

Financial support from Fondo di Ateneo ex-60% UniBS and FLEX FCT grant PTDC/EGE-ECO/108547/2008 is gratefully acknowledged.

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