The Value of Transferable Skills*

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Abstract
Most studies on skill transferability focus on the return to capabilities developed in the initial
job and disregard the different characteristics of the origin and the destination industries. In
contrast, this paper assesses the borders of skill transferability by comparing the return to
skills for firm stayers, firm changers in the same industry and firm changers to other
industries. Based on a sample of Portuguese employees in retail banking, our results confirm
significant inter-firm and inter-industry skill transferability. Difference-in-differences
estimates with propensity score matching show that firm switchers benefit from a wage
premium compared to firm stayers. However, the wage premium drops sharply when movers
leave the banking sector.

Keywords: skill transferability, retail banking, wage, difference-in-differences, propensity
score matching

JEL: J24, J31, J62

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I. Introduction

Over the past decades, human capital theory has played an important role in our understanding of the wage premium attached to specific types of skill (Becker, 1964). Depending on skill fungibility, human capital theory discriminates between general skills, useful in virtually all workplaces, and specific skills, required by selected employers only. The opposition between general skills and specific skills provided support for models of the labor market that long affected theoretical and empirical research, such as internal labor markets (Doeringer and Piore, 1971) or labor market signaling (Spence, 1973). Nevertheless, a radical contrast between general and specific skills has been repeatedly questioned in more recent years. Since the initial acknowledgement of an intermediate category of transferable skills between firm-specific and general skills (Shaw, 1987; Stevens, 1996), researchers have highlighted the role played by industry-specific skills (Neal, 1995; Parent, 2000), occupation-specific skills (Shaw, 1987; Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009; Zangelidis, 2008; Sullivan, 2010) and task-specific skills (Gathmann and Schönberg, 2010).

This literature supports the existence of non-negligible though heterogeneous returns to industry-specific experience that significantly overlap and interact with occupation-specific and task-specific experience. However, the large majority of the studies on skill transferability across firms and industries focus on the return to capabilities developed in the initial job and disregard how the different characteristics of the origin and the destination industries may constrain the transferability of an employee’s skills and impact her/his wage. In contrast, this paper aims to assess the borders of skill transferability by comparing the return to skills for firm stayers, firm changers in the same industry, and firm changers to other industries.
The sector-specific empirical analysis provided in this paper focuses on the retail banking industry, which was highly regulated in the past (Eriksson and Werwatz, 2005; Seltzer, 2010) and more recently exposed to intense institutional, technological and organizational change (Hunter et al., 2001). The accelerated industrial dynamics, characterized by new entries, mergers and acquisitions, and the digitalization of information flows, involving both competence-enhancing and competence-destroying change, highlight the importance of skill transferability for the long-term employability of the labor force in retail banking. In addition, evidence on the return to industry-specific skills in retail banking is mixed and calls for further investigation. For instance, Kletzer (1996) supports the transferability of the skills developed in finance and services by showing that pre-displacement tenure from these sectors involves a higher return than tenure accumulated in other sectors. On the other hand, Zangelidis (2008) provides evidence in support of skill specificity by reporting banking and finance as the only sector that recognizes a significant wage premium for industry-specific experience.

Our empirical analysis is based on Quadros de Pessoal, a longitudinal archive of linked employer-employee data on the Portuguese labor market that allows an employee’s career across years and across subsequent employers to be tracked. Difference-in-differences estimates with propensity score matching on retail banking white collar workers show that, on average, firm switchers benefit more from a wage premium than firm stayers. However, the wage premium drops sharply when movers leave the banking sector. The rest of the paper is organized as follows. Section II surveys the literature on transferable skills and details our research hypothesis. Section III outlines our empirical strategy and section IV presents the data. Section V reports the empirical evidence and section VI draws our conclusions from this study.
II. The return to transferable skills

While there is agreement on the general meaning of transferable skills among scholars, significant differences arise in operational definitions. Stevens (1996) frames transferable skills as an intermediate category between general and specific skills whose applicability goes beyond the borders of the firm, though it is restricted to a limited cluster of employers. Sullivan (2010) recalls Becker’s dichotomy of completely general versus specific skills, yet he discriminates between firm-specific, occupation-specific and industry-specific skills. Kletzer (1996) refers to industry-specific skills as a special form of transferable skills. Lazear’s skill-weights approach also infers the transferable nature of skills. All skills have a general nature, but the special combination of skills required to perform a particular task at a certain workplace turn them into specific skills (Lazear, 2003).

Research on skill transferability across employers has been triggered by the question of whether displaced workers suffer a wage loss when re-entering the labor market. The underlying assumption is that the less transferable the skills provided by an employee, the higher the post-displacement wage loss she/he will experience (Addison and Portugal, 1989). The first attempts to quantify the costs of the loss of firm-specific skills for displaced workers date back to the late 1980s. The natural set to test the impact of skill transferability on wages was soon recognized in job mobility, especially by means of direct comparisons between industry stayers and industry switchers (Podgursky and Swaim, 1987; Addison and Portugal, 1989; Neal, 1995; Kletzer, 1996). Neal (1995) provides evidence of the higher post-displacement wage losses suffered by industry switchers compared to industry stayers. Weinberg (2001) suggests that the recruitment of experienced workers endowed with industry-specific skills is less sensitive to industry shocks than in the case of less experienced younger workers. Based on longitudinal datasets, Parent (2000) provides additional evidence of the higher return to industry-specific skills compared to that of firm-specific skills.
A recent evolution of this literature has explored the wage consequences of employer and industry changes not only in the case post-displacement re-employment, but also for voluntary job-to-job transitions (Light and McGarry, 1998; García Pérez and Rebollo Sanz, 2005; Light, 2005; Longhi and Taylor, 2013). For instance, García Perez and Rebollo Sanz (2005) and Longhi and Taylor (2013) compare the wage dynamics of voluntary and involuntary movers and show that unemployment associated with involuntary job change generates wage losses because of negative signals embodied in layoffs or scarring effects, whereas voluntary movers generally experience positive returns to mobility. However, few contributions explore the link between voluntary mobility and skill transferability. Available studies indicate that workers with higher seniority are less likely to move (Topel, 1991), also after controlling for individual heterogeneity (unobserved ability and propensity to move) and job-match heterogeneity (Altonji et al., 2013). Other studies question whether the accumulation of occupation-specific or industry-specific skills impact job mobility. Empirical findings suggest that workers with low levels of industry tenure are less likely to change industry because learning about one’s own productivity takes time. Zangelidis (2008) provides evidence of higher mobility across occupations than across industries, whereas Battisti (2013) reports variation in the probability of changing industry according to the duration of industry-specific experience.

In contrast with the above contributions, other studies argue that a dichotomization between industry stayers and industry switchers cannot provide a full picture of skill transferability across industries (Kletzer, 1996). Movers face a range of alternatives and their final choice is affected by multiple drivers. Pack and Paxson (1999) suggest that physical proximity and similarity in processes and labor flows significantly condition labor mobility patterns. Workers are willing to move to closer industries in order to better exploit their accumulated skills and receive higher wages. Kletzer (1996) and Cha and Morgan (2010)
show that the reward for transferable skills varies with the destination industry. Ong and Mar (1992) report that displaced workers from Silicon Valley companies rehired in the same 4-digit industry suffer no wage loss, whereas the earnings of those re-employed outside high-tech industries fall sharply.

In summary, many studies report substantial heterogeneity in the earnings of firm switchers depending on the re-employment industry. Accordingly, when a heterogeneous effect of the re-employment industry on wage is assumed, measuring this heterogeneity becomes a crucial research target. Kletzer (1996) estimates the wage change between pre-displacement and post-displacement jobs by destination industry and suggests that firm switchers’ earnings are conditioned by wage patterns in the re-employment industry. In a similar way, Cha and Morgan (2010) show that re-employment in traditional low-wage industries involves a wage loss, whereas Ong and Mar (1992) highlight the need to identify the borders between “close” and “far away” industries in subsequent employment contracts.

Despite the insights offered by the above studies, systematic research on inter-industry distance and its impact on the wage of industry switchers is still lacking. A more rigorous use of the metaphor of distance to describe similarity/dissimilarity in transferred skills is provided by studies on occupational mobility (e.g., Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009). The distance between subsequent occupations is measured by comparing occupation-specific tasks and skills listed by occupation directories like the U.S. Dictionary of Occupational Titles. This approach allows for direct and quantitative comparisons between all possible pairs of occupations, provided that they are described in the same occupation directory. However, the heavy reliance upon a specific classification tool (i.e., the occupation directory) limits the extension of this approach to other levels of analysis such as the industry level.
To test the borders of skill transferability from the banking industry we will assess the relative wage premium (or wage loss) of firm switchers who move to a new job in industries progressively more distant from their source industry. The underlying assumption is that highly firm-specific skills have no value outside the workplace where they were developed and no external employer is expected to pay for them. On the other hand, fully transferable general skills are expected to be acknowledged and rewarded by any employer outside the source firm. In the case of partial skill transferability, non-negative returns can be expected when the old and the new employer make use of similar technologies, procedures and tools. Our research hypothesis is that industry matters in the transferability of firm switchers’ skills. The greater the distance between the industries of source and destination employer, the higher the share of lost skills and consequently the lower the return to transferable skills.

III. 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 employer and experience in the current industry, whereas Neal (1995) provides separate estimates of the return to pre-displacement tenure for displaced employees who either find a new job in their original industry or move to a different sector. These approaches provide evidence of 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 the borders of skill transferability to be assessed, i.e., how far an employee can move from the original workplace before her/his skills lose value for potential employers.

Equation (1) shows a simple model for testing the limits of skill transferability. $\omega_t$ is the wage received by employee $i$ at time $t$, $\overline{M}_t = \{M_{1,t}, M_{2,t}, \ldots, M_{H,t}\}$ is a vector of $H$ binary
variables accounting for recent employer and industry change, $\bar{Z}_u$ is a vector of control variables and $\epsilon_u$ is the error term.

$$\ln \omega_u = \beta_0 + M_h \beta_1 + Z_u \beta_2 + \epsilon_u \quad (1)$$

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.

Despite the simple functional form, the estimate of equation (1) presents substantial empirical challenges. The choice of moving to a different employer and possibly to a different industry is endogenous with respect to wage after change (Kletzer, 1996; García Perez and Rebollo Sanz, 2005). Differences in the distribution of skills, attitudes and motivations affect the probability to select into treatment, i.e. to switch firm. At the same time, skills, attitudes and motivations also play the role of significant wage drivers. For instance, proactive workers may engage in job search and improve their wage thanks to higher individual productivity resulting from a better job match. Omitting significant determinants of both job mobility and earnings entails significant biases in the OLS estimate of the coefficients of equation (1). Instrumental variables are often used to overcome the potential biases due to selection on unobserved/observable variables (Imbens and Wooldridge, 2009; Parent, 2000). However, the identification of a suitable set of instruments for all the binary variables that account for possible moves to new employers and new industries in equation (1) looks particularly challenging.

Propensity Score Matching (PSM) provides an alternative approach for identifying the average impact of job mobility for firm switchers compared to that of firm stayers. PSM,
originally developed to assess the causal effects of policy measures in natural experiments, compares the average outcomes observed for a set of treated individuals and a control group based on a set of pre-treatment characteristics affecting both the observed outcome and the probability of selection into treatment. The core idea, the so-called conditional independence or unconfoundedness assumption, is that “adjusting treatment and control groups for differences in observed covariates, or pretreatment variables, removes all biases in comparisons between treated and control units” (Imbens and Wooldridge, 2009, p.7). A matching mechanism based on a function of pre-treatment observable variables rules out systematic differences between treated and untreated individuals and allows for an unbiased estimate of the average treatment on the treated. The computational difficulty of matching similar treated and untreated individuals increases with the dimension of vector X. However, Rosenbaum and Rubin (1983) prove that conditional independence is still valid if controlling for the probability of participation based on the X covariates, rather than on vector X. Lechner (2001) extends Rosenbaum and Rubin’s findings to the case of multiple 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 labor market programs for young Swedish workers.

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 capturing the probability of participation by means of pre-treatment observable variables X, a condition that is hard to meet in the case of

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1 For recent surveys, see Caliendo and Kopeinig (2008) and Imbens and Wooldridge (2009).
2 Additional applications of PSM with multiple treatments are provided by Dorsett (2006), who assesses the impact of four programs of subsidized 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 on the early career of Spanish workers.
unobservable individual heterogeneity. In addition, PSM does not account for possible time
trends unrelated with the treatment. When information on output is available for treated
individuals and for the control group both before and after the former are exposed to the
treatment, these problems can be solved by a difference-in-differences (DID) approach. DID
estimates compare the average gain in output for the treated after and before the treatment to
the average gain enjoyed by the control group in the same time period. This double
differentiation – across groups and across time – accounts for both unobserved time-invariant
differences between treated and untreated individuals and for time trends independent of the
considered treatment (Imbens and Wooldridge, 2009).

Nevertheless, the applicability of DID estimators is also limited by strong constraints.
DID estimators assume that, in the case of no treatment, the average outcome of treated
individuals would have followed the same time trend observed for the control group,
irrespective of a possible imbalance in the distribution of pre-treatment characteristics
affecting the output of treated and untreated individuals (Abadie, 2005). Thus, the
combination of propensity score matching with difference-in-differences methods (PSM-
DID) provides a promising solution to account for both unobserved heterogeneity, treatment-
independent time trends and unbalanced distribution of observable pre-treatment
characteristics associated with the observed outcome among individuals in the 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 labor economics and education economics confirms the interest of researchers in
exploring the potentialities of these tools to solve problems of selection on observables,
selection on non-time variant unobservables and independent time trends. However, with the
notable exception of Davia (2010), the existing contributions focus on binary treatments and

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3 See, e.g., Blundell et al. (2004), Bergemann et al. (2009), Buscha et al. (2012).
neglect the multiple treatment case, apt for modeling the multiple alternatives available to a firm/industry switcher.

A convenient semi-parametric estimator for testing the average treatment on the treated in case of multiple treatments is provided by Abadie (2005). Consider participation in \( \mathcal{H} \) mutually exclusive treatments and a two time period 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, \( Y_t(1) \) 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, \( Y_0(0) = Y_0(1) \) \( \forall h \in \mathcal{H} \). Under the assumption that, conditional on a set of covariates \( X \), the average outcome for treated and untreated individuals would have followed parallel paths in the absence of treatment and the overlap assumption that for each given value of the covariates both treated and controls can be observed, Abadie (2005) shows that the average treatment on the treated (ATT) for treatment \( h \) compared to the counterfactual of untreated individuals can be modeled as

\[
\tau_{ATT} = E \left\{ \frac{(Y_1 - Y_0)}{P(H = h)} \left( h - h_0 \ast \frac{P(H = h|X)}{1 - \sum_{j \in \mathcal{H}} P(H = j|X)} \right) \right\} \tag{2}
\]

In equation (2), \( Y_1 \) 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 \( h \in \mathcal{H} \); \( h_0 \) is a binary variable equal to 1 if the observed individual is exposed to no treatment; \( P(H = h) \) is the unconditional probability of treatment \( h \) in the sample; \( P(H = h|X) \) is the individual propensity score for treatment \( h \) given a set of \( X \) covariates; and \( 1 - \sum_{j \in \mathcal{H}} P(H = j|X) \) is the individual propensity score for no treatment\(^4\).

\(^4\) Equation (2) is based on equation (10) in Abadie (2005, p.8), extended to the case of different levels of treatment according to the indications provided in the section on “Multi-level treatments” (pp.10-11). Abadie focuses on multi-level treatments, i.e., increasing doses of the same treatment to stress the possibility of
Equation (2) shows that treated and untreated observations are balanced through a weighting scheme based on propensity scores to treatment, which increase when the values taken by the covariates are over-represented among the treated and vice-versa. In other words, Abadie’s estimator increases the weight of untreated observations similar to treated observations along the covariates profile (i.e., untreated observations with high propensity scores) and weights down the outcome gain displayed by untreated observations with low propensity scores.

A consistent and $\sqrt{N}$-asymptotically normal estimator of the average treatment on the treated for treatment $h$ can be calculated as in (3)

$$\hat{\tau}_{ATT} = \frac{1}{N} \sum_{k=1}^{N} \left( \frac{(Y_{1-h} - Y_0)}{p(H=h)} \ast \left( h - h_0 \ast \frac{\hat{p}(H=h|X)}{1 - \sum_{j \neq H} \hat{p}(H=j|X)} \right) \right)$$  \hspace{1cm} (3)

where $N$ is the number of individuals either in treatment $h$ or in no treatment. In the case of binary treatment, the estimator in (3) can be re-written as

$$\hat{\tau}_{ATT} = \frac{1}{N} \sum_{k=1}^{N} \left( \frac{(Y_{1-h} - Y_0)}{p(D=1)} \ast \left( \frac{D - \hat{p}(D=1|X)}{1 - \hat{p}(D=1|X)} \right) \right)$$  \hspace{1cm} (4)

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

The estimator proposed by Abadie (2005) presents significant 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. Thus, post-matching tests of covariate balance between treated and control group are not required and no observations are lost due to balancing mechanisms. In addition, the extension to the case of multiple treatments makes this estimator suitable for testing the wage effect of generalizing the proposed approach to continuous treatments. However, under the unconfoundedness assumption and the overlap assumption the semi-parametric approach suggested by Abadie can be extended from the binary case to the multiple case also when the identified mutually exclusive treatments represent unordered alternatives rather than different levels of the same treatment (Imbens and Wooldridge, 2009, p.73).
moving to a different employer and possibly a range of different industries compared to a counterfactual sample of firm stayers.

IV. Data

The data used in the empirical assessment of the boundaries of skill transferability from the Portuguese banking industry are provided by Quadros de Pessoal (QdP), a longitudinal dataset that includes the population of Portuguese firms with at least one wage earner and their employees in private manufacturing and services sectors.\(^5\) Thanks to unique employer and employee codes, QdP allows employer and employee information to be matched and employees’ careers to be followed across subsequent employers.

QdP has been widely used to explore demand-side and supply-side wage determinants (Cardoso, 2000; Cardoso and Winter-Ebmer, 2010) and match quality between workers and firms (Lima and Pereira, 2003; van der Klaauw and Dias da Silva, 2011; Torres et al., 2013). Stylized facts on the Portuguese labor market supported by QdP include long-term orientation of employment relationships, the concentration of job separations in early careers and negative correlation between job mobility and both tenure and education (Lima, 2004).

For the purpose of the following analysis, the identification of retail banking firms is based on a 3-digit industry code and includes all companies listed in the area of monetary intermediation.\(^6\) Our sample includes full-time permanent white-collar workers employed at

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\(^5\) Data are collected annually by the Portuguese Ministry of Employment. For additional details, see Cardoso and Portela (2009).

\(^6\) Banking firms with a change in activity classification code between 2002 and 2009 were excluded from the analysis, as were banks where no labor outflows to other firms were recorded in the same period. Due to significant differences in mission and strategy compared to retail banking firms, we also excluded observations from the Portuguese Central Bank. QdP records 50,257 individuals employed at least once in a full-time permanent white-collar job at the selected retail banking firms between 2002 and 2008.
least once at a Portuguese retail bank between 2002 and 2008 and still in employment one year later, either with the same employer or with another firm. Each observation concerns the employment situation of an individual in two subsequent years. To avoid an over-representation of specific employee groups, the dataset used in the empirical analysis includes one observation per unique employee code. One-time firm switchers are observed the last year with their original employer and one year later. In the case of firm stayers, we randomly selected one observation for each unique employee code reported to stay with the same employer two or more years between 2002 and 2008. Random selection of one observation per unique employee code was also applied in the case of multiple firm switchers.

To assess the return to inter-firm mobility, an employer change can be framed as a treatment, whereas firm stayers provide the control group. When accounting for the destination industry, firm switch corresponds to a multiple treatment as an employee could either sign a new contract with another banking firm or move to a different industry.

Measuring the distance between destination industries and the banking sector is crucial for testing our hypothesis on inter-industry skill transferability. The proposed classification of firm switchers is based on the employer industry codes provided by QdP\(^7\). We identify firm switchers to other companies in the area of monetary intermediation (same 3-digit industry as the source firm) as moves within the retail banking industry. In the Portuguese classification of economic activities in use until 2006, the 3-digit sector of “Other financial intermediation” belongs to the same 2-digit sector of “Monetary intermediation”, whereas “Insurance, reinsurance and pension funding” and “Other financial activity services” are the 2-digit industries classified immediately after “Monetary intermediation”. As a result,\(^7\) QdP follows the 5-digit industry classification adopted by the Portuguese National Institute of Statistics (CAE, Classificação das Atividades Económicas).
we classify changes to the above areas of employer as moves to firms providing financial services. All other changes of employer are classified in the residual categories of moves outside the financial industry.

Our empirical analysis focuses on intra-industry and inter-industry job-to-job transitions. However, QdP provides no information about the reasons behind the interruption of an employment contract. Consequently, we are not able to discriminate between voluntary and involuntary separations. Nevertheless, employer records by QdP confirm that no Portuguese banking firm closed down between 2002 and 2009 and, in contrast with most recent years, no massive layoffs are recorded in the same period. By examining employer records, we detected 13 acquisitions where at least 90% of the workforce of the acquired company was absorbed by the buying company without interruption of tenure tracks. All mergers and acquisitions in the Portuguese banking industry between 2000 and 2010 were accompanied by negotiations with trade unions aimed at protecting employment levels (Esteves, 2008; Silva, 2009). In addition, interviews with trade unions and bank officers confirmed the centrality of job security in the Portuguese banking industry during the years examined and the willingness to avoid dismissals in situations of corporate restructuring. We can therefore exclude involuntary firm changes due to bank mergers. Meanwhile, we cannot exclude that a share of firm changers left their full-time permanent position involuntary following a breach of discipline or other contract rules. However, involuntary separations are reported to represent a marginal share of total separations in the Portuguese banking industry in the early 2000s (Esteves, 2008).

Wage dynamics are affected significantly 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 (Farber, 1999). To avoid possible biases due to the approaching retirement from the labor market, we discarded observations of individuals above 55 years of age. In addition, we removed observations on 1.5% top and bottom earners by 1-digit occupation and observations with missing information on wage, working hours or job. The resulting database includes 40,200 observations from 26 banking firms, 4,033 of which concern firm switchers.

Table 1 displays the observed job transitions from the banking industry by initial job. The persistence of internal labor markets in Portuguese retail banks in the early 2000s is witnessed by the large prevalence of firm stayers compared to that of firm changers. About 90% of observed employees experienced no firm change. Contrary to findings for the overall Portuguese labor market (Andersen et al., 2008), employees with higher skills (managers, professionals and technicians) display a higher than average propensity to move outside the financial sector.

Tables 2 and 3 provide some preliminary evidence on hourly gross wage premium and wage losses associated with different types of employment mobility\(^8\). Table 2 shows that, on average, the wage of firm switchers is slightly higher in their former job than the wage of firm stayers, but this difference is not statistically significant. However, their more substantial

\(^8\) QdP reports the total gross wage paid to employees in the month when data are collected (typically October) and the corresponding regular working time and overtime. Deflated gross hourly wages in euros (base 2008) were obtained as the ratio of total gross deflated monthly wage to total worked hours. The total gross monthly wage includes variable components such as bonuses, whose distribution may significantly differ between stayers and new entrants. However, our data show that in two subsequent years the percentage incidence of the variable components on total wage changes, on average, by only 0.66%, with no significant difference between firm stayers and firm changers at the .05 level (t=1.715, p=0.087). Nonetheless, should bonus or other variable payments occur in a month other than October, these elements of bankers’ compensation will not be captured by the available data.
wage increase on moving to a different employer provides them with higher wages at their new employer, compared to those of firm stayers. Table 3 provides separate comparisons for wage levels and wage growth experienced by 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 switchers are a rather heterogeneous group and that comparisons limited to firm stayers and firm switchers may hamper the identification of more articulated dynamics. If employees who move to other banking firms start from the highest average wage gap and enjoy the highest average premium, gains get smaller when bank white-collar workers move to less closely related industries, with non-significant mean wage growth in the case of movers to firms in the financial sector and significant mean wage increases for movers outside the financial sectors. Nevertheless, the wage gains experienced by the latter are much smaller than those enjoyed by firm switchers who remain in the banking industry. 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.

V. Empirical results

Following Abadie (2005), the empirical analysis to test the return to firm and industry mobility from the Portuguese banking industry entails two steps. The first step concerns the calculation of the individual propensity score, i.e., the probability of participating in cross-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 the case of binary treatment, when firm switchers are compared with firm stayers irrespective of their destination industry, and in the case of multiple treatments, when the
analysis is detailed for movers to other retail banks, movers to the finance industry and movers outside the finance industry.

The overlap assumption requires that some fraction of the population is exposed to all levels of treatment and that untreated individuals are observed for all values of the covariates (see Assumption 3.1 in Abadie, 2005, p.7). This constraint restricts our sample, but only negligibly (from 40,200 to 40,076 observations). In addition, propensity score matching provides reliable results as long as the balancing score actually captures the probability of receiving a treatment. The rich set of pre-treatment observable covariates provided by QdP enhances the chance of controlling for factors that affect the probability of receiving a treatment and achieving the observed outcome. Definition and descriptive statistics for the covariates used to calculate individual propensity scores to binary and multiple treatments are provided in Table 4.

In line with past literature, we calculate covariate-based propensity scores by means of a binary logistic model for the binary treatment (see, e.g., Blundell et al., 2004; Dorsett, 2006) and a multinomial logit model for the multiple treatment (see, e.g., Lechner, 2002; Larsson, 2003; Davia, 2010). Table 5 reports 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. The model displays a satisfactory prediction power, with over 92% of cases correctly classified and a pseudo $R^2$ of 0.258. In line with the results from past literature, inter-firm mobility decreases with tenure, age at the time of recruitment by the initial employer and firm size, and female employees display lower mobility compared to their male colleagues. In contrast with the general findings on the Portuguese labor market (Garcia Pérez and Rebollo Sanz, 2005; Andersen et al., 2008), and possibly due to the peculiar concentration of higher educational and skill profiles in the banking industry, educational qualification displays a
positive (despite a non-significant) coefficient and the propensity to move to a new firm is significantly stronger among employees with higher hierarchical positions.

As a result of the concentration of value-added services in the metropolitan area of Lisbon which characterizes the Portuguese economy, we also control for the geographical location of the employer in the first period of time. However, contrary to our expectations the more favorable employment opportunities provided by the district of Lisbon, which account for 47.9% of total observations and 57.6% of firm switchers, are not a significant determinant of firm change (Table 5).

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. The logarithmic difference between wage in the first time period and the average wage of other employees classified in the same 6-digit job code provided an additional significant determinant of firm switch\(^9\) (Ln \(dwage_{peers}\) in Table 5). As expected, the higher the wage differential with peers in the same job, the higher the probability of moving to another employer within one year.

An additional variable accounts for the relative attractiveness of the destination industry compared to the source industry. Attractiveness, calculated as the difference in yearly employment growth rates between the destination industry and the banking industry\(^10\), is a strong and significant determinant of the probability to move to a different employer. A

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9 We verified that at least 20 observations were recorded in QdP for each 6-digit job code.

10 Relative attractiveness is calculated at the 3-digit level for the finance industry and at the 2-digit level for other sectors. The value of this variable is obviously null for movers to other banking firms, whereas mean values are 0.204 and 0.058, respectively, for movers to the finance industry and movers outside the finance industry.
1% increase of employment in the destination sector compared to the banking industry raises the odds of changing firm compared to staying in the same job by 32%.

The binary logistic regression also controls for fixed year effects, for the collective labor agreement in force at the initial employer and for firm fixed effects. Both year controls, labor agreement controls and firm fixed effects are jointly significant determinants of the probability of selection into the binary treatment.

The propensity score for multiple treatment is calculated through a multinomial logistic regression where the reference category is represented by firm stayers as opposed to moving to another banking firm, moving to a firm in the financial industry and moving to a firm in other industries (Table 6). The multinomial logistic regression explains a high percentage of variance in the data (pseudo $R^2$ equal to 0.289) and displays a satisfactory classification power (Table 7). This is a crucial requirement to estimate the average treatment on the treated based on the proposed estimator, because inaccurate propensity scores result in unreliable estimates of outcome gains. The percentage of correctly classified cases ranges from 99.2% for firm stayers, to 10.9% for movers to other firms in the banking sector, to 41.0% for movers to the finance industry, to 53.9% for movers outside the finance industry\textsuperscript{11}.

The multinomial logistic model “breaks up” the category of firm switchers into three distinct sub-groups. The use of this model is thus reliable as long as the assumption of the independence of irrelevant alternatives is respected (Larsson, 2003). The comparison between

\textsuperscript{11} Our figures are much higher than those reported by Larsson (2003), for instance, who calculates correct classification rates between 6.8% and 76.1%. In addition, it has to be noted that the correct classification rate obtained with the proposed classification of firm switchers proved to be much higher compared to that of other solutions. For instance, merging the adopted definition of financial services with the 2-digit industry of “Business services” resulted in a drop of over 10% in the overall rate of correctly classified observations. Similar results were obtained by splitting movers outside the banking industry into switchers to the manufacturing sector and the services sector.
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.

The examination of the coefficients of the multinomial regression reveals interesting differences among firm switchers by destination industry. First, the differential between the employment growth rate in the destination industry and in the banking sector is a powerful driver of the propensity to leave the banking industry (see the coefficient of the Attractiveness variable in Table 6). A 1% increase in this differential raises the odds of moving to the financial sector by 49% compared to the odds of remaining with the same employer and increases the odds of moving outside banking and financial firms by 47%. The high value and the strong 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).

In line with past literature, higher initial tenure and higher recruitment age with the original employer 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 significantly increases the propensity to change employers, but only for workers who move to another retail bank or outside the financial sector (see the coefficient of variable Ln dwage peers in Table 6). This outcome suggests that employees may look for “ability-sensitive employers” in a similar workplace when they feel under-appreciated (Groshen, 1991), whereas they may pursue a radical change when they feel they have the wrong skills in their initial workplace. The comparison between the coefficients that signal residence in the district of Lisbon shows that the non-significant effect reported for the binary estimate results from the composition of opposite effects. Location in the Lisbon district negatively affects the odds of switching to
another bank. However, probably due to the concentration of financial services and corporate headquarters in the Portuguese capital city compared to the rest of the country, this variable is a significant determinant of the propensity to move outside the banking industry. Finally, manager and professional positions display the highest propensity to switch firm, especially for movers outside the finance industry.

Table 8 reports the difference-in-differences estimates of the return to firm mobility calculated according to formula (4) in section III, for binary treatment, and to formula (3), for multiple treatment. All standard errors are bootstrapped with 500 repetitions. The first panel of Table 8 shows that after controlling for pre-treatment differences and for individual unobserved heterogeneity, firm switchers still benefit from a significantly better wage increase compared to firm stayers. However, when the average treatment on the treated accounts for the destination industry (second panel of Table 8), it becomes apparent that the overall picture is the sum of significantly segmented patterns. On average, movers to other retail banks benefit from the highest wage increase in relations to the counterfactual group of firm stayers. A significant relative wage increase also accrues to workers who move to a new employer in the financial industry, even though the size of the benefit is slightly over one fifth compared to firm switchers who remain in the banking industry. Moreover, employees who move outside the banking and the finance sector experience a significant advantage over comparable firm stayers and their gain is larger than in the case of switchers to a firm in the finance industry. However, the small difference between the estimated wage gains (about 0.50 gross euros per hour for movers to finance and about 0.75 gross euros per hour for movers outside finance) justified an additional investigation on the relative outcome of movers outside the banking industry. 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). For this reason we replicated formula (4) to estimate both the
relative wage gain of movers to finance versus movers outside finance and the relative wage
gain of movers outside finance versus movers to finance. The results of the additional
analyses support a statistically significant difference between the relative outcomes of these
treatment groups. Abadie’s approach detects a significant wage loss for movers to finance in
relation to movers to other sectors (estimated differential gains = -1.504 gross euros per hour,
z=-2.83, p<0.01) and a corresponding wage advantage for movers outside finance in relation
to movers to finance (differential gains = -0.728 gross euros per hour, z=2.77, p<0.01). This
evidence suggests that industry matters, but similarity between procedures, processes and
techniques in the origin and the destination industry is not the only driver of skill
transferability.

The results displayed in Table 8 provide substantial support to the hypothesis of skill
transferability from the banking sector. Also when moving to employers in markedly
different sectors, the skills provided by former bank employees are valued by their new
employers and, at least in the short run, their wages display significant increases compared to
the option of remaining with the original employer. At the same time, the decline in the
advantage perceived by firm switchers who leave the banking 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 banking firms
that are willing to pay a wage differential to attract readily-operative employees. However,
the re-usability of skills declines as banking employees move to industries characterized by
more diversified processes and outputs.

VI. Concluding remarks

Increasing job volatility, rising training costs and more frequent organizational and
technological change focus the attention of labor market players on transferable skills.
Transferable skills increase workers’ employability and provide firms with ready-to-use competences and capabilities to fill opening and vacant positions. Assuming that transferable skills will be signaled by a non-negative wage progression of firm switchers compared to that of firm stayers, this paper tested the borders of transferability for the skills developed within retail banking, a sector traditionally described as a collection of internal labor markets characterized by firm-specific skills.

In contrast with the prevailing approach in the literature for appraising the return to inter-industry mobility, we claim that both source and destination sectors matter. Differences in technologies, techniques and labor flow organization between the source and the destination industry lower the probability of inter-industry skill transfer. We account for the difference between source and destination sector by modeling firm change as a multiple treatment based on the distance between retail banking and the sector where firm switchers find new employment. To assess the relative wage premium of firm switchers in relation to that of firm stayers accounting for observed and unobserved individual heterogeneity, we implemented a DID-PSM approach for a multiple treatment. To the authors’ knowledge, this paper provides the first implementation of Abadie’s semi-parametric difference-in-differences PSM estimator for a multi-treatment case (Abadie, 2005).

Our empirical findings show that firm switchers benefit from mobility. On average, firm switchers enjoy a significant wage premium vis-à-vis that of the counterfactual group of firm stayers. Benefits are higher for employees who move to another retail bank, but the average wage growth enjoyed by firm switchers is higher than the wage growth experienced by firm stayers also when moving outside the original industry. This outcome supports the hypothesis of significant inter-firm and inter-industry transferability of the professional skills developed within the borders of the banking sector. Our analysis also shows that the average wage gain of movers outside the banking and financial industry is significantly higher than
the gain enjoyed by movers to firms in the financial sector. The non-linearity of decline in wage gains with distance from the banking industry draws attention to the importance of exploring non-industry related factors such as occupation-specific skills (Kambourov and Manovskii, 2009).

Under the lens of job matching theory, the stronger wage increase of firm switchers compared to firm stayers supports the idea that workers sort into jobs according to their comparative advantage. At least in the case of employees from the Portuguese retail banking industry, our findings sustain intra-industry and inter-industry matching predictions. However, the nature of transferred skills is a source of friction, as demonstrated by the lower wage growth experienced by movers who leave the banking sector.

In general terms, our results question the traditional vision of retail banking as a source of industry-specific, if not firm-specific, skills. Indeed, our findings depict banking as a training sector for transferable skills and a potential skill supplier for the entire economy. However, the low figures for firm switchers and industry switchers (10.9% and 3.1% of total observations, respectively) call for some caution in extending and generalizing our results. In the case of increased competitiveness of internal and external labor markets in the banking industries, competing banks and non-banking firms may be unable to absorb all firm leavers, thus frustrating their investment in transferable skills. At the same time, higher turnover and quit rates may induce banking firms to review their internal training policy and turn to external sourcing to fill vacant positions.

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References


Davia, M.A. (2010), Job Mobility and Wage Growth at the Beginning of the Professional Career in Spain, *Revista de Economia Aplicada* 18(52), 5-34.


### Table 1. Observed job transitions from the retail banking industry

<table>
<thead>
<tr>
<th>Occupation in first time period</th>
<th>Treatment level</th>
<th>Firm stayers</th>
<th>Firm changers</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Firm stayers</td>
<td>Move to banking</td>
<td>Move to finance</td>
<td>Move outside finance</td>
</tr>
<tr>
<td>Managers</td>
<td>No. obs.</td>
<td>2,560</td>
<td>168</td>
<td>102</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>88.1%</td>
<td>5.8%</td>
<td>3.5%</td>
</tr>
<tr>
<td>Professionals</td>
<td>No. obs.</td>
<td>892</td>
<td>46</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>89.7%</td>
<td>4.6%</td>
<td>1.7%</td>
</tr>
<tr>
<td>Technicians</td>
<td>No. obs.</td>
<td>11,388</td>
<td>939</td>
<td>221</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>88.9%</td>
<td>7.3%</td>
<td>1.7%</td>
</tr>
<tr>
<td>Clerical workers</td>
<td>No. obs.</td>
<td>21,327</td>
<td>1567</td>
<td>375</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>90.8%</td>
<td>6.7%</td>
<td>1.6%</td>
</tr>
<tr>
<td>Total</td>
<td>No. obs.</td>
<td>36,167</td>
<td>2,720</td>
<td>715</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>90.0%</td>
<td>6.8%</td>
<td>1.8%</td>
</tr>
</tbody>
</table>

### Table 2. Wage differentials between firm stayers and firm changers

<table>
<thead>
<tr>
<th>Firm changer</th>
<th>N</th>
<th>Mean</th>
<th>Std.dev.</th>
<th>Std. Error Mean</th>
<th>t-test for equality of means</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>d.f.</td>
</tr>
<tr>
<td>Total hourly wage in $t_0$</td>
<td>No</td>
<td>36,167</td>
<td>13.614</td>
<td>6.527</td>
<td>0.034</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>4,033</td>
<td>13.756</td>
<td>6.185</td>
<td>0.097</td>
</tr>
<tr>
<td>Total hourly wage in $t_1$</td>
<td>No</td>
<td>36,167</td>
<td>14.117</td>
<td>6.824</td>
<td>0.036</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>4,033</td>
<td>16.154</td>
<td>6.825</td>
<td>0.107</td>
</tr>
<tr>
<td>$\Delta$ total hourly wage between $t_0$ and $t_1$</td>
<td>No</td>
<td>36,167</td>
<td>0.504</td>
<td>1.670</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>4,033</td>
<td>2.398</td>
<td>3.508</td>
<td>0.055</td>
</tr>
</tbody>
</table>

* *** p< 0.01 ** p< 0.05 * p< 0.10: deflated wages (€, base=2008); (a) equality of variances assumed; (b) equality of variances not assumed

### Table 3. Wage differentials by destination industry

<table>
<thead>
<tr>
<th>ANOVA F-test</th>
<th>Total hourly wage in $t_0$</th>
<th>Total hourly wage in $t_1$</th>
<th>$\Delta$ total hourly wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>14.663 ***</td>
<td>117.688 ***</td>
<td>1,598.739 ***</td>
</tr>
</tbody>
</table>

** Games-Howell test for multiple comparisons**

<table>
<thead>
<tr>
<th>Mean difference</th>
<th>Std. Error</th>
<th>Mean difference</th>
<th>Std. Error</th>
<th>Mean difference</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Move to banking vs. Firm stayer</td>
<td>-0.278 0.115 *</td>
<td>2.338 0.123 ***</td>
<td>2.616 0.059 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Move to finance vs. Firm stayer</td>
<td>0.570 0.255 **</td>
<td>0.779 0.270 **</td>
<td>0.209 0.112</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Move outside finance vs. Firm stayer</td>
<td>1.540 0.293 ***</td>
<td>2.165 0.365 ***</td>
<td>0.625 0.196 ***</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* *** p< 0.01 ** p< 0.05 * p< 0.10; 40,200 observations; deflated gross hourly wages (€, base=2008)
<table>
<thead>
<tr>
<th>Covariate</th>
<th>Description</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tenure t0</td>
<td>Tenure before treatment [years]</td>
<td>8.683</td>
<td>7.694</td>
</tr>
<tr>
<td>Squared tenure t0</td>
<td>Squared tenure before treatment</td>
<td>134.594</td>
<td>205.616</td>
</tr>
<tr>
<td>Education years t0</td>
<td>Education before treatment [years]</td>
<td>13.689</td>
<td>2.904</td>
</tr>
<tr>
<td>Age hire t0</td>
<td>Age at recruitment before treatment [years]</td>
<td>29.160</td>
<td>7.103</td>
</tr>
<tr>
<td>Ln firm size t0</td>
<td>Natural logarithm of firm size before treatment [employees]</td>
<td>8.219</td>
<td>1.067</td>
</tr>
<tr>
<td>Ln dwage peers t0</td>
<td>Natural logarithm of the difference between individual yearly gross wage before treatment and the average wage of other employees in the same 6-digit job code [€, base=2008]</td>
<td>-0.055</td>
<td>0.258</td>
</tr>
<tr>
<td>Attractiveness t0</td>
<td>Differential in employment growth rate between destination and source industry</td>
<td>0.006</td>
<td>0.055</td>
</tr>
<tr>
<td>Gender</td>
<td>Takes value 1 for female employees</td>
<td>41.4</td>
<td></td>
</tr>
<tr>
<td>Lisbon t0</td>
<td>Takes value 1 for before treatment employer in the Lisbon district</td>
<td>48.5</td>
<td></td>
</tr>
<tr>
<td>Manager t0</td>
<td>Takes value 1 for managers before treatment</td>
<td>7.2</td>
<td></td>
</tr>
<tr>
<td>Professional t0</td>
<td>Takes value 1 for professional occupations before treatment</td>
<td>2.5</td>
<td></td>
</tr>
<tr>
<td>Technician t0</td>
<td>Takes value 1 for technical occupations before treatment</td>
<td>31.9</td>
<td></td>
</tr>
<tr>
<td>Clerical worker t0</td>
<td>Takes value 1 for clerical occupations before treatment</td>
<td>58.4</td>
<td></td>
</tr>
</tbody>
</table>

40,076 observations; * Occupation reference category in econometric estimates

---

### Table 5. The drivers of propensity to firm change

<table>
<thead>
<tr>
<th>Covariate</th>
<th>( \beta )</th>
<th>( \text{Std. Dev.} )</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.809</td>
<td>(0.419)                 *</td>
<td></td>
</tr>
<tr>
<td>Education years t0</td>
<td>0.006</td>
<td>(0.008)                 ***</td>
<td></td>
</tr>
<tr>
<td>Tenure t0</td>
<td>-0.059</td>
<td>(0.012)                 ***</td>
<td></td>
</tr>
<tr>
<td>Squared tenure t0</td>
<td>-0.003</td>
<td>(0.001)                 ***</td>
<td></td>
</tr>
<tr>
<td>Age hire t0</td>
<td>-0.081</td>
<td>(0.004)                 ***</td>
<td></td>
</tr>
<tr>
<td>Ln firm size t0</td>
<td>0.060</td>
<td>(0.060)                 ***</td>
<td></td>
</tr>
<tr>
<td>Ln dwage peers t0</td>
<td>1.061</td>
<td>(0.082)                 ***</td>
<td></td>
</tr>
<tr>
<td>Attractiveness t0</td>
<td>28.310</td>
<td>(2.246)                 ***</td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>-0.382</td>
<td>(0.042)                 ***</td>
<td></td>
</tr>
<tr>
<td>Lisbon t0</td>
<td>0.029</td>
<td>(0.041)                 ***</td>
<td></td>
</tr>
<tr>
<td>Manager t0(^{a})</td>
<td>0.145</td>
<td>(0.088)                 *</td>
<td></td>
</tr>
<tr>
<td>Professional t0(^{a})</td>
<td>0.355</td>
<td>(0.130)                 ***</td>
<td></td>
</tr>
<tr>
<td>Technician t0(^{a})</td>
<td>0.158</td>
<td>(0.047)                 ***</td>
<td></td>
</tr>
</tbody>
</table>

\(-2\) Log likelihood: 19341.68
Pseudo R\(^2\): 0.258

**Dependent variable:** Firm changer; binary logistic regression; robust standard errors in parenthesis;

40,076 observations; *** \(p < 0.01\) ** \(p < 0.05\) * \(p < 0.10\).

Regression includes controls for fixed year effects, fixed firm effects and collective labor agreements

\(^{a}\) Reference category: Clerical workers in \(t_0\).
Table 6. The drivers of propensity to firm and industry change

<table>
<thead>
<tr>
<th></th>
<th>Move to banking</th>
<th>Move to finance</th>
<th>Move outside finance</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>β</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>1.373 (0.392)</td>
<td>-4.164 (0.825)</td>
<td>-0.874 (0.676)</td>
</tr>
<tr>
<td>Education years t0</td>
<td>-0.002 (0.009)</td>
<td>0.060 (0.020)</td>
<td>0.028 (0.017)</td>
</tr>
<tr>
<td>Tenure t0</td>
<td>0.022 (0.016)</td>
<td>-0.093 (0.021)</td>
<td>-0.181 (0.023)</td>
</tr>
<tr>
<td>Squared tenure t0</td>
<td>-0.008 (0.001)</td>
<td>0.003 (0.001)</td>
<td>0.003 (0.001)</td>
</tr>
<tr>
<td>Age hire t0</td>
<td>-0.103 (0.004)</td>
<td>-0.023 (0.009)</td>
<td>-0.046 (0.007)</td>
</tr>
<tr>
<td>Ln firm size t0</td>
<td>0.144 (0.049)</td>
<td>0.119 (0.102)</td>
<td>-0.374 (0.084)</td>
</tr>
<tr>
<td>Ln dwage peers t0</td>
<td>1.161 (0.093)</td>
<td>0.075 (0.206)</td>
<td>1.098 (0.190)</td>
</tr>
<tr>
<td>Attractiveness t0</td>
<td>-0.168 (0.482)</td>
<td>40.202 (3.417)</td>
<td>38.583 (3.022)</td>
</tr>
<tr>
<td>Gender</td>
<td>-0.449 (0.047)</td>
<td>-0.213 (0.103)</td>
<td>-0.349 (0.093)</td>
</tr>
<tr>
<td>Lisbon t0</td>
<td>-0.132 (0.045)</td>
<td>0.937 (0.107)</td>
<td>0.572 (0.097)</td>
</tr>
<tr>
<td>Manager t0(a)</td>
<td>0.020 (0.108)</td>
<td>0.175 (0.176)</td>
<td>0.771 (0.163)</td>
</tr>
<tr>
<td>Professional t0(a)</td>
<td>0.273 (0.165)</td>
<td>-0.006 (0.308)</td>
<td>1.075 (0.202)</td>
</tr>
<tr>
<td>Technician t0(a)</td>
<td>0.261 (0.053)</td>
<td>-0.492 (0.128)</td>
<td>0.564 (0.099)</td>
</tr>
</tbody>
</table>

-2 Log likelihood 23,407.66
Pseudo R² 0.289

Reference category of the dependent variable: Firm stayer; multinomial logistic regression; robust standard errors in parenthesis; 40,076 observations; *** p < 0.01 ** p < 0.05 * p < 0.10.

Regression includes controls for fixed year effects, firm fixed effects and collective labor agreements

(a) Reference category: Clerical workers in t0.

Table 7. Predictive power of the multinomial logit model

<table>
<thead>
<tr>
<th>Observed</th>
<th>Predicted</th>
<th>Firm stayers</th>
<th>Move to banking</th>
<th>Move to finance</th>
<th>Move outside finance</th>
<th>Percent Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm stayers</td>
<td></td>
<td>35,868</td>
<td>199</td>
<td>0</td>
<td>0</td>
<td>99.4%</td>
</tr>
<tr>
<td>Move to banking</td>
<td></td>
<td>2,412</td>
<td>294</td>
<td>0</td>
<td>0</td>
<td>10.9%</td>
</tr>
<tr>
<td>Move to finance</td>
<td></td>
<td>358</td>
<td>11</td>
<td>292</td>
<td>52</td>
<td>41.0%</td>
</tr>
<tr>
<td>Move outside finance</td>
<td></td>
<td>215</td>
<td>11</td>
<td>46</td>
<td>318</td>
<td>53.9%</td>
</tr>
</tbody>
</table>

Table 8. The return to firm mobility – PDM-DID estimates of wage increase

<table>
<thead>
<tr>
<th></th>
<th>Differential total gross hourly wage</th>
<th>Bootstrap std. error</th>
<th>Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Binary treatment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm switchers vs. Firm stayers</td>
<td>1.759</td>
<td>0.068</td>
<td>25.99   ***</td>
</tr>
<tr>
<td>Multiple treatment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Movers to banking vs. Firm stayers</td>
<td>2.288</td>
<td>0.080</td>
<td>38.75   ***</td>
</tr>
<tr>
<td>Movers to finance vs. Firm stayers</td>
<td>0.485</td>
<td>0.119</td>
<td>4.08    ***</td>
</tr>
<tr>
<td>Movers outside finance vs. Firm stayers</td>
<td>0.754</td>
<td>0.185</td>
<td>4.07    ***</td>
</tr>
</tbody>
</table>

*** p < 0.01; Deflated gross hourly wages (€, base=2008); 40,076 observations