The Earnings Effects of Entrepreneurial Experience in Creative Occupations

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Abstract: We investigate the earnings effect from job mobility into creative occupations and test for the importance of prior entrepreneurial experience. Our analysis employs doubly robust difference-in-difference estimation for Danish register data, which enables us to control for confounding factors of human capital. We find that prior experience as self-employed is pivotal for positive earnings effects when taking up creative occupations after a job change. While our estimates do not indicate an unconditional increase in earnings from job mobility, the increase conditional on entrepreneurial experience is up to 27 percent. Entrepreneurial experience is essential for earnings in creative occupations.

Keywords: Entrepreneurial experience, earnings, creative occupations, job mobility, difference-in-difference estimation

JEL codes: M13, M51, M54, J3, J4

1. Introduction

Knowledge on job opportunities and earnings outcomes in post-entrepreneurial dependent remains inconclusive (Evans and Leighton, 1990; Williams, 2000; Hamilton, 2000). While on strand of entrepreneurship research points to the role of sector-specific experience of entrepreneurs and sectoral dynamics as an influencing factor for earnings outcomes (Kaiser and Malchow-Møller, 2011; Cambell, 2013; Luzzi and Sasson, 2016), other strands of the literature focus on tasks and skills as an important conditioning factor (Baptista, Lima and Preto, 2012). Experience from self-employment is shown to be important for entry and promotion into certain types of occupations in dependent work with leadership and supervision tasks. Though equally important from an employee an employer perspective, however, the earnings effect of such prior experience in different occupations remain largely unexplored. This is what we attend to here.

We consider a type of occupational heterogeneity, which has been widely used for regional analysis and which is based on the concept of the so-called 'creative class', e.g. Florida (2002, 2004, and 2005). The 'creative class' concept proposes a new way to measure latent talents and skills relevant for individual job outcomes based on occupational categories. While it has advanced for the understanding of knowledge-, technology- and entrepreneurship-driven urban growth processes, it has also been critically debated in the literature. As, for instance, Glaeser (2005) argues, defining the creative class based on occupational information may just deliver an alternative indicator for education levels. The creative class concept has consecutively been refined and operationalized in Boschma and Fritsch (2009). The authors define different groups of creative occupations based on ILO's ISCO codes of occupation types. Selected occupations are characterized by creating new ideas, new technology and/or new creative content or engage in complex problem solving under independent judgement. Fujiwara, Dolan and Lawton (2015) classify characteristics of creative occupations combining autonomy (self-determinacy, engagement), competence (usefulness, impact) and freedom (openness to ideas, unconventionality). We accordingly adapt the classification by Boschma and Fritsch (2009) of occupations predominately used for regional analysis to the individual and firm level.

The classification of Boschma and Fritsch (2009) is here used as a measure of occupational heterogeneity with a creative orientation and we ask if experience as self-employed increases earnings in such particular types of occupations. Our general hypothesis is that experience from self-employment is a particular type of human capital which increases earnings in creative occupations compared to non-creative occupations. The endeavor is therefore less to provide new evidence on the regional development potential from the 'creative class' concept, but rather to test our hypothesis at the individual and firm level in a rigorous empirical identification strategy, as discussed in Maula and Stam (2019). We develop a new estimation approach controlling for amongst others educational attainment to provide evidence robust to the critique that occupational heterogeneity only reflects differences in education. We acknowledge that estimating earnings effects from entrepreneurial experience is complicated. Particularly, as processes of selection in and out of entrepreneurship relate to underlying personality traits, which may be defined broadly or more narrowly (see e.g. Leutner et al., 2014). Also, the experience from entrepreneurial exits may be of importance in terms of successful and unsuccessful exits (Strese, Gebhard, Feierabend and Brettel, 2018).

Given that such underlying personality traits and other underlying factors are time invariant, we argue that including individual-level fixed effects in the empirical estimation strategy for (individual level) panel data controls for such selection issues. Evidence point to possible changes over the life course of some traits (see e.g. Roberts, Walton and Veichtbauer, 2006), why we also control for possible biases from such unobservable characteristics and possible changes over the life course by adding time-varying individual characteristics to our model (details will be given in Section 4). Our focus is on analyzing job changes into creative occupations and job changes into non-creative occupations compared to job stayers in non-creative jobs. This introduces another concern in terms of selection bias, i.e. are selection processes into creative occupations different from those into non-creative occupations? To control for such non-random job mobility determinants, we use a propensity score-based weighting procedure (e.g. Abadie, 2005). We accordingly apply a doubly robust difference-in-difference estimator. The empirical approach developed here is based on previous contributions on earnings effects in post entrepreneurial employment facing similar challenges of controlling for selection biases (e.g. Kaiser and Malchow-Møller, 2011).

We use Danish register data from 2006 to 2011 to the analysis of earnings effects of prior experience as self-employed when switching jobs into a creative occupation. Working with Danish register data, besides offering a large sample size for effect identification, has the advantage that Denmark ranks second on low regulatory barriers with respect to starting your own business (World Bank, 2019). A low regulatory barrier to become self-employed reduces obstacles to gain experience as self-employed for all potential individuals. This may also alleviate concerns about selection biases.

Our results show that job changes between firms from non-creative occupations to creative occupations are generally not associated with significant changes in earnings. Changes in earnings from job changes from non-creative occupations to creative occupations are roughly 2 percent below the average evolution of earnings in the comparison group, i.e. persons with similar characteristics except that they do not switch jobs between employers and continue to work in a non-creative occupation. However, we find that the experience as self-employed increases earnings after job changes between employers from non-creative occupations to creative occupations. The earnings effect of entrepreneurial experiences in creative occupations is up to 27 percent relative to the comparison group of job stayers. These effects vary by educational attainment with the largest effect observed for low-/medium-skilled employees. We take this to show that experience as self-employed substitutes for other types of (formal) human capital components in terms of earnings effects.

Secondly, we find that experience as self-employed only has an earnings effect for job changes into creative occupations but not into non-creative occupations. This indicates that experience as self-employed has a unique effect on the ability to create value in creative occupations, not seen in their non-creative counterparts. We therefore provide new evidence that elaborates on the findings in Baptista, Lima and Preto (2012) and Failla, Melillo and Reichstein (2017) pointing to the importance of hierarchies in earnings and skills for the effects of experience from self-employment. Finally, we show that time-varying firm-level contexts are important for earnings (Antonietti, 2013; Audretsch and Belinski, 2013), but the results on the importance of experience from self-employment for earnings in creative occupations are robust to the inclusion of such contextual factors.

While one may argue that any occupational classification is to some extent *ad hoc*, we find very clear evidence that the occupational heterogeneity proposed by Boschma and Fritsch (2009) matters for the earnings effects of experience from self-employment. This evidence is important from a policy perspective. A very clear positive post-entrepreneurial earnings effect points to the individual and societal importance of furthering entrepreneurship through e.g. entrepreneurial education even if self-employment spells are short and income low during self-employment (see e.g. Rosen, 1981; Hamilton, 2000; Hyytinen, Ilmakunnas and Toivanen, 2013). Important parts of the gains from entrepreneurship are harvested in the post-entrepreneurial period of entrepreneurial careers in a set of particular occupations. We leave it to future research to investigate how personality traits relate to such occupations, which renders such higher earnings. Our approach does not allow us to identify this link apart from controlling for unobservable heterogeneity at the individual level.

The remainder of the paper is structured as follows. Section 2 shortly reviews the theoretical background of the earnings effects of experience from self-employment and effects from occupational heterogeneity discussed in the literature and state a conditional and an unconditional hypothesis. In Section 3 we present the research methodology used in the analysis in terms of data and treatment group definitions, which is followed by a discussion of the empirical strategy for causal inference in Section 4. Thereupon, we turn to results on the effects of job change between employers to creative occupations on earnings and the importance of prior experience as self-employed. The final section offers a discussion and conclusion.

2. Theoretical Background

Our research focuses on the earnings effects from prior experience as self-employed in the event of a simultaneous job change across firms and occupations. The earnings effect of prior experience as self-employed during this type of job change is accordingly at the heart of the analysis.

2.1 Job Changes, Entrepreneurial Experience and Earnings

Job changes may either increase or decrease earnings depending on the extent of an initially inferior job match or a higher human capital accumulation (Burdett, 1978; Mortensen, 1988). Earnings differentials between dependent workers and entrepreneurs are at least 30-40 percent (Hamilton, 2000; Hyytinen, Ilmakunnas and Toivanen, 2013) but may vary by start-up motives (van Stel, Millán, Millán, and Román, 2018). Experience as self-employed may be interpreted as an investment into human capital that renders a higher or lower return than experience in dependent work. The literature has generally found a negative wage effect of previous self-employment (Ferber and Waldfogel, 1998; Williams, 2000, 2002; Bruce and Schuetze, 2004; Hyytinen and Rouvinen, 2008). Kaiser and Malchow-Møller (2011) also find a negative effect on hourly wages except for experience as self-employed in the same sector as the sector of the subsequent dependent work. Compositional dimensions may therefore matter in matching job market competences from self-employment experience.

Using the framework of task-specific human capital (Gibbons and Waldmann, 2006), the experience as self-employed is in Baptista, Lima and Preto (2012) shown to increase the entry into employment and promotion to higher levels of occupations in the firm's hierarchy. Specifically, experience from self-employment is important for the recruitment and promotion to occupations, where leadership or supervisory/coordination tasks and skills dominate. While Baptista, Lima and Preto (2012) do offer insights into earnings effects of previous business ownership, they do not consider if such earnings effects are conditional on tasks and skills in occupations. The earnings penalty from the experience of founding a new business is in Failla, Melillo and Reichstein (2017) shown to apply for low earnings quantiles while being absent in the 90th percent earnings quantile. At the same time, individuals with experience as self-employed see a lower probability of changing affiliation relative to wageworkers. This does not directly attend issues of occupations, tasks and skills but hints at some of the hierarchical advantages for persons that have experience from self-employment.

2.2 The Role of Occupational Heterogeneity

Experience from self-employment may be important for the earnings effects in specific types of occupations. Which occupational heterogeneity captures such earnings effects? One approach would be to stress the earnings and promotion dynamics from task/skill-specific human capital (Gibbons and Waldmann, 2006). Our approach relates to a different literature originally focusing on regional growth. Several contributions have used the concept of a creative class as a driver for regional growth. In this literature, Florida (2002, 2004, and 2005) proposes a broader concept of human capital that not only incorporates individual talents and skills but also accounts for the way these talents and skills are utilized by firms and the regional economy.

Boschma and Fritsch (2009) operationalize this by pointing to groups of specific occupations that may be described as creative types of occupations. In this sense, it is another measure of occupational heterogeneity, which may be important for earnings effects from experience in self-employment. We note that our approach does not attempt to address underlying individual factors of creativity, but addresses the importance of experience as self-employed for such creative types of occupations.

Expecting higher earnings from experience as self-employed for those occupations related to these occupations being closer to creating value in firms through e.g. innovation (e.g. Kirzner, 1979, Alvarez and Busenitz, 2001). Luzzi and Sasson (2016) find that rewards to experience from self-employment depend on the extent to which industries are dynamic and innovative. De Jong, Parker, Wennekers, and Wu (2015) point to the importance of entrepreneurial behavior in dependent work, which depends on job autonomy, hereunder innovation and proactivity in the job design. Similarly, Sorgner (2015) establishes a link between entrepreneurship-prone personalities and occupational choices. This takes the importance from experience in self-employment in the direction of linking this experience to occupational choices that creates value and innovation in firms. In addition, Antonietti (2013) shows the importance of creative human capital spillovers relates to the work environment for innovativeness. The creativity theory of knowledge spillover entrepreneurship for urban contexts is along similar lines tested in Audretsch and Belinski (2013).

2.3 Earnings and Entrepreneurial Experience in Creative Occupations

Based on our general hypothesis that prior experience from self-employment matters for earnings in creative occupations, we provide new evidence on two specific hypotheses. A first hypothesis points to *unconditional* effects on earnings from job mobility into creative occupations. A second hypothesis makes the earnings effect of job mobility into creative occupations *conditional* on experiences from self-employment. This is what we test empirically.

A well-known caveat in addressing the wage effects in specific occupations is a discussion on, whether occupations measure education. Glaeser (2005) is critical to the extent that economic effects from creative types of occupations can be ascribed to the extent that talents and skills are utilized by firms and the regional economy, but rather just reflects an underlying formal educational attainment by different individuals. Moving from general earnings effects in Baptista, Lima and Preto (2012), to earnings effects for specific occupations, such issues must be considered in detail. Our empirical approach addresses these issues.

3. Research Methodology

One of the challenges in identifying the earnings effects related to job mobility (into creative or non-creative occupations) and the moderating role of entrepreneurial experience is that of proper data and identification. For instance, given the flexibility and dynamics of labor markets, it must be secured that such job changes are unique to avoid biasing the estimation results when simultaneous or overlapping other labor market events happen. Moreover, individuals in the treatment group(s) must be compared with a relevant comparison group, i.e. with individuals that have similar characteristics except that they do not change jobs. We also want to control for individual contexts that may confound the effects of entrepreneurial experience, which contributes to the detail of data required.

3.1 Data and Variables

To obtain reliable evidence on the interplay between entrepreneurial experience, job mobility into creative occupations and the development of individual earnings, we need detailed and consistent data on each individual's career history (education, entrepreneurial experience, labor market status) and the job environment (job inflow rates of firm, share of creative occupations in the firm). All this requires that data should be longitudinal to identify previous entrepreneurial experiences and subsequent job changes among firms between non-creative and creative occupations.

We use the register data from Statistics Denmark (DST) that cover all individuals between 16 and 70 years of age active in the labor market. Four databases from DST are combined to offer sufficient information for identification: 1) BEF (Befolkningen/Population), which contains information about population and population change; 2) RAS (Registerbaserede arbejdsstyrkestatistik/Register based labor market statistic) which comprises the population's labor market status, earnings, employer characteristics and job mobility; 3) UDDA (Uddannelser) which contains detailed information about educational qualifications of the population and 4) STORHED (Bystørrelse/city size) representing the population of cities in Denmark. Our dependent variable measures earnings in dependent employment in Danish kroner (DKK). For our empirical analysis, we further construct measures of creative occupations, entrepreneurial experience and other control variables that are defined below.

3.1.1 Job Mobility into Creative and Non-Creative Occupations

To define a measure of job mobility into creative occupations, we rely on an occupation-based concept as proposed in Boschma and Fritsch (2009). The exact occupational types associated with the creative occupations are listed in Table A1 (Appendix A). We use DISCO (Danish International Standard Classification of Occupations) occupational codes from DST, which is the Danish version of the ILO’s ISCO for this categorization. Based on this measure of creative occupations, we then construct a treatment variable that tracks job changes across employers from either a non-creative occupation to a creative occupation or from a non-creative to a non-creative occupation. An individual is associated with a creative occupation if working in a profession that is included in the ISCO occupation list used by Boschma and Fritsch (2009) as shown in Appendix A.

3.1.2 Prior Entrepreneurial Experience

The concept of entrepreneurial experience is used to measure a specific component of human capital, which originates from the theory of entrepreneurship by Schumpeter (1911). In empirical terms, measuring entrepreneurial activity leading to entrepreneurial experience can either be done at the individual or the firm level (Gartner and Shane, 1995). While the measurement at the firm level is mainly concerned with different types of organizational and new firm formation, individual-specific measures typically focus on the different stages of self-employment including the individual's engagement in a startup and the ownership/management of a new firm (Justo, De Castro and Maydeu-Olivares, 2008). For the purpose of this study, we focus on registered self-employment in the official DST register data. This implies that the individual has been the owner/manager of a firm and that this activity constituted the individual's main economic activity at that time. The main reason for our focus on full-time entrepreneurship is that this concept can be expected to better capture the acquisition of entrepreneurial competences that may be beneficial in creative occupations (Fujiwara, Dolan, and Lawton, 2015).

We therefore use self-employment to identify entrepreneurs in the register data based on labor market status (see Acs, Audretsch, and Evans, 1994; Blanchflower and Oswald, 1998; Parker and Robson, 2004; Glaeser, 2005; Stephens and Partridge, 2011). Given the longitudinal structure of our register data, this allows us to identify individuals that at some point in time have been active as self-employed persons but at later stages have changed to dependent work.

3.1.3 Additional Control Variables

Besides these main variables, we use several other variables to control the observable heterogeneity across individuals and firms. Concerning firm-level characteristics, the first covariate we used is the firm's share of creative occupations out of total employment. A stronger concentration of individuals in creative occupations at the firm level may, as a contextual factor, be important for the earnings potential from a job change into a creative occupation. Second, we use the job inflow rate, which is measured as the number of new jobs offered in the firm for a given year out of total employment. Changes in earnings may depend on the firm being in an upwards development trend, stagnant or downward trend. Both such contexts may be important for the prevalence of human capital and knowledge spillovers at the firm level. We also control for firm size measured as the total number of employees in the firm, as earnings may depend on the size of firms (Coles, 2001; Haltiwanger, Hyatt, Kahn, and McEntarfer, 2018). Finally, we include measures of city size, as rich literature points to the importance of agglomeration effects for earnings in creative occupations.

Concerning the individual characteristics, we control for age, education and full-time employment which may influence individual earnings as evident in the literature (Mincer and Polachek, 1974; Gullason, 1990; Becker, 1964). Age is measured in years and full-time employment is a binary dummy variable. To assess the impact of individual education, we used three categories: high, medium and low educations. A detail description of all variables together with their summary statistics is presented in Table A2 of the appendix.

3.2 Specification of Treatment and Comparison Groups

For a given individual, a job change between firms may take place at any point in time from 2007 to 2011 (we use the first sample year 2006 as a baseline for our propensity score estimations, see below). We focus on individuals that only have one such job change during the period from 2007 to 2011. This gives us unique events, which allows us to study the earning effects from job mobility into creative occupations mobility vis-à-vis job stayers in a difference-in-difference (DiD) estimation setup. We define two types of treatment groups: 1) job mobility into creative occupations, 2) job mobility into non-creative occupations. For job mobility into creative occupations, individual moves from a non-creative occupation to creative occupation while changing employer. Similarly, job mobility into non-creative occupations measures the job change from one employer to another but remaining in a non-creative occupation. Our comparison group consists of individuals that remain at the same employer and stays in non-creative occupation throughout the period. Given the discussion of whether creative occupations are different from education (Glaeser, 2005), we restrict individuals in both treatment groups and the comparison group to remain at the same education level throughout the sample period.

Table 1: Description of Comparison and Treatment Groups

#	**Description**	***Comparison Group***	***Creative***	***Non-Creative***	***Creative × Entre***	***Non-Creative × Entre***
1	Constant education level throughout the sample period	✓	✓	✓	✓	✓
2	No job change throughout the sample period	✓				
3	Job change from non-creative to creative occupation		✓		✓	
4	Job change from non-creative to non-creative occupation			✓		✓
5	Entrepreneurial experience prior to job change				✓	✓

We define five conditions that we impose differently on the comparison group and the two treatment groups as shown in Table 1. The comparison group must fulfill the conditions in Column 1 of Table 1. The first treatment group capturing job mobility into creative occupations (*Creative*) is defined under Column 2. This groups remains at the same educational level throughout the sample period and has one job change from a non-creative occupation at one employer to a creative occupation at another employer. The second treatment group covers individuals that change jobs between firms but continue to work in a non-creative occupation (*Non-Creative)*. Again, this group remains at the same education level throughout the sample period and is defined under Column 3.

The earnings effects for both treatment groups are also estimated conditional on entrepreneurial experience (*Entre*) defined as having been self-employment before changing jobs into a creative or non-creative occupation and then never returns to self-employment. These effects are represented as *Creative* × *Entre* and *Non-Creative* × *Entre* and are defined in Columns 4 and 5 respectively. Importantly, all treatment effects are measured relative to individuals that remain with the same employer and in a non-creative occupation throughout the sample period (*Comparison Group*). Notice that individuals that never change jobs and stay in a creative occupation are excluded from the sample.

4. Estimation Strategy

Our empirical identification strategy builds on the estimation of Mincer-type earnings equations as a widely used empirical tool in the field of labor economics (Mincer, 1974). At the center of attention is the analysis of earnings effects of job changes into creative and non-creative occupations. To properly estimate the magnitude of such effects, the estimated earnings equations control for individual and firm-level characteristics, as well as, other determinants of individual earnings levels. Following Gabe, Colby and Bell (2007) and D'Costa and Overman (2014) among others, we employ a general panel data modelling framework of the following form

$$\ln(earnings_{i,t}) = \alpha_i + \tau_t + \gamma Creative_{i,t} + \beta'\mathbf{X}_{i,t} + \delta'\mathbf{Z}_{i,t} + \varepsilon_{i,t} \tag{1a}$$

$$\ln(earnings_{i,t}) = \alpha_i + \tau_t + \rho Non\text{-}Creative_{i,t} + \beta'\mathbf{X}_{i,t} + \delta'\mathbf{Z}_{i,t} + u_{i,t}, \tag{1b}$$

where $\ln(earnings_{i,t})$ is the log of annual earnings for individual *i* in period *t*. $\mathbf{X}_{i,t}$ and $\mathbf{Z}_{i,t}$ are vectors of individual and firm-level characteristics (including a set of industry dummies), respectively, with β and δ being the associated coefficient vectors; α_i and τ_t are individual- and time-fixed effects to control for time-constant latent individual treats and time-specific variations common to all individuals (e.g. macroeconomic shocks or business cycle movements). We accordingly estimate three-way fixed effects panel data models to control for unobservable individual, industry and time specific characteristics. Finally, the variable $Creative_{i,t}$ in equation (1a) is a binary dummy measuring the timing of job changes into a creative occupation in a classical difference-in-difference manner (Lechner, 2011). The variable takes a value of 1 if the individual undertakes a job change into a creative occupation at time *t* and remains so for the rest of the sample period. In similar veins, $Non\text{-}creative_{i,t}$ in equation (1b) is a binary indicator variable taking value 1 if the individual changes jobs from and to a non-creative occupation; $\varepsilon_{i,t}$ and $u_{i,t}$ are standard *i.i.d.* error terms for both earnings equations.

When estimating equation (1a) and equation (1b) we are mainly interested in quantifying γ and ρ as coefficients for the average treatment effects for treated individuals (i.e. those switching jobs between two firms from a non-creative to a creative occupation in equation (1a) and from and to a non-creative occupation in equation (1b)). Given that earnings levels have been log-transformed, the two coefficients γ and ρ can be interpreted as the average percentage earnings increase (for $\gamma > 0, \rho > 0$) or earnings decrease (for $\gamma < 0, \rho < 0$) for treated individuals relative to those in the comparison group (i.e. job stayers in non-creative occupations).

As an extension to the standard earnings equations shown in equation (1a) and equation (1b), we are particularly interested to see whether entrepreneurial experience (*Entre)* works as an essential moderating variable for the magnitude of the estimated effects. To do so, we compute interaction terms between the binary dummy variables for *Creative* and *Non-Creative* and the individuals' entrepreneurial experience *(Entre)*, respectively. The coefficients of these interaction terms then measure the additional earnings impact of job mobility into creative or non-creative occupations for individuals with prior entrepreneurship experience on top of the unconditional marginal effect of job mobility on individual earnings. Formally, the extended regression equations can then be written as

$$\ln\left(earnings_{i,t}\right) = \alpha_i + \tau_t + \gamma Creative_{i,t} + \varphi\left(Creative_{i,t} \times Entre_i\right)$$
$$+\beta'\mathbf{X}_{i,t} + \delta'\mathbf{Z}_{i,t} + \varepsilon_{i,t} \tag{2a}$$
$$\ln\left(earnings_{i,t}\right) = \alpha_i + \tau_t + \rho Non\text{-}Creative_{i,t} + \theta\left(Non\text{-}Creative_{i,t} \times Entre_i\right)$$
$$+\beta'\mathbf{X}_{i,t} + \delta'\mathbf{Z}_{i,t} + u_{i,t} \tag{2b}$$

with φ and θ being the coefficients of the included interaction terms $\left(Creative_{i,t} \times Entre_{i,t}\right.$ and $\left.Non\text{-}creative_{i,t} \times Entre_{i,t}\right)$. The overall earnings effect of job mobility into a creative or non-creative occupation for an individual with prior entrepreneurship experience can accordingly be calculated as $\gamma + \varphi$ for creative occupations and $\rho + \theta$ for non-creative occupations. The coefficients γ and ρ measure the earnings effects for treated individuals without prior entrepreneurial experience.

As benchmark specification, we estimate the above shown Mincer-type earnings equations by means of ordinary least squares (OLS) within the framework of a two-way fixed effects model (FEM). However, a potential drawback of OLS estimation is that it assumes that differences between treated and non-treated individuals can be fully eliminated through the inclusion of observable characteristics ($\mathbf{X}_{i,t}\mathbf{Z}_{i,t}$) in the linear regression equation. This linearity assumption may not be sufficient to balance the treated and non-treated groups and thus lead to biased estimation of treatment effects in the light of self-selection effects. To reduce the risk of a selection bias into certain types of job mobility, we therefore also estimate the earnings equations as doubly robust conditional difference-in-difference (CDiD) model, which combines propensity score matching with DiD estimation (see, for instance, Heckman, Ichimura, Smith et al., 1998, Abadie, 2005, Sant'Anna and Zhao, 2018). The latter has the advantage that only one of two – weights derived from propensity score regression or inclusion of covariates in second stage DiD specification - need be correctly specified to obtain an unbiased effect estimator (Funk, Westreich, Wiesen, et al., 2001, for a general overview of doubly robust estimation).

CDiD regressions are carried out in a two-step manner. The first step estimates the propensity that an individual will change jobs to a creative or non-creative occupation (π_i) in later sample periods as a function of observable individual ($\mathbf{X}_i$) and firm-level ($\mathbf{Z}_i$) characteristics in the initial sample period. We run the first-step estimations on the basis of a Probit model. The obtained propensity score values from the Probit regressions are then used to construct sample weights for the estimation of the second step DiD model by means of weighted least squares (WLS). This weighting scheme creates a synthetic sample which ideally balances the observed baseline covariates between the two treatment groups and the comparison group.[1] We apply the CDiD estimator to the earnings equations shown in equation (1a) to equation (1b) and equation (2a) to equation (2b).

5. Empirical Results

5.1 Earnings effects of entrepreneurial experience from job mobility

[1] The use of propensity score weights for estimating treatment effects is based on two conditions (see, for instance, McCaffrey, Griffin, Almirall et al., 2013): First, each individual has a non-zero probability of receiving each treatment and second, the set of observed pre-treatment covariates is sufficiently rich, such that it includes all variables directly influencing the treatment and outcome variable.

What are the earnings effects of job mobility into creative occupations compared to job mobility into non-creative occupations and does entrepreneurial experience matter for these effects? We initially consider results based on the unconditional model that offers general insights into whether job mobility into creative occupations contributes to individual earnings. Columns (1) to (4) in Table 2 accordingly present the DiD model results for the FEM estimator incorporating individual- and time-fixed effects according to equation (1a) and equation (1b). To investigate the importance of entrepreneurial experience (*Entre*), we subsequently consider a conditional model with interaction terms in equation (2a) and equation (2b). Columns (5) to (8) in Table 2 tests the hypothesis that entrepreneurial experience is a particular type of human capital, which is conducive to adding value and increase earnings in creative occupations. Panel A of Table 2 presents our main results for job mobility into creative occupations (*Creative*) and the importance of entrepreneurial experience (*Entre*). Panel B offers similar results for job mobility into non-creative occupations (*Non-creative*) for comparison.

Job mobility is generally associated with lower earnings levels. Earnings decline for job mobility into create occupations by roughly 2 percent, as shown in Column (2) of Panel A in Table 2. Adding more control variables to the regression specification reduces this effect. Results can be interpreted within the context of search behavior and initial inferior job matches that makes the individual accept a reduction in earnings from the job change between firms irrespective of previous entrepreneurial experience. A better job match after the job change may on the other hand increase future expected earnings.

The results for conditional effects from entrepreneurial experience on earnings differences associated with job mobility into creative occupations are reported in Columns (5) to (8) of Panel A in Table 2. The unconditional effect of job mobility to creative occupations (γ in equation (2a)) in column (6) remains a negative earnings effect of roughly 2 percent (*Creative*). Adding entrepreneurial experience (*Entre*) in an interactive term with the treatment variables for job mobility into creative occupations, the effect of entrepreneurial experience is sizeable and increases earnings by at least 27 percent. The combined measure of the unconditional and conditional effects ($\gamma + \varphi$ in equation (2a)), i.e. the overall earnings increase for job switchers into creative occupations with prior entrepreneurial experience, is significant and at about 26 percent. Having entrepreneurial experience is therefore pivotal for the earnings effects from job mobility into creative occupations.

Are effects of entrepreneurial experience a general labor market mechanism or are they specific to creative occupations? This is answered in Panel B of Table 2 showing the treatment of job mobility into non-creative occupations. Job mobility into non-creative occupations reduce earnings by up to 10 percent irrespective of entrepreneurial experience, which is a larger earnings reduction than the reduction of up to 2 percent for a job mobility into a creative occupation. While job mobility among firms generally leads to lower earnings, the reduction is much smaller for job mobility into creative occupations.

The effect of entrepreneurial experience in Panel B of Table 2 is not significant for the interaction term (*Non-Creative* × *Entre*). Thus, we get clear-cut empirical findings: While entrepreneurial experience is of sizeable and positive importance for job mobility into creative occupations, this is absent for job mobility between non-creative occupations. Entrepreneurial experience is a particular type of human capital increasing productivity in creative occupations. Our results contribute by capturing underlying dynamics relative to the focus on industry sectors in e.g. Kaiser and Malchow-Møller (2011) from occupational heterogeneity across industries. The current results provide evidence of such underlying dynamics with respect to the value of entrepreneurial experience for creative occupations.

Table 2: Earnings Effects of job changes with and without entrepreneurial experience

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Dependent variable (in logs):	Earnings	Earnings	Earnings	Earnings	Earnings	Earnings	Earnings	Earnings

Estimation	DiD	DiD	DiD	DiD	DiD	DiD	DiD	DiD
PANEL A: Job Mobility into Creative Occupations								
Creative **(indicator)**	-0.004 0.003	-0.021*** 0.003	-0.008** 0.003	-0.007** 0.003	-0.004 -0.003	-0.021*** -0.003	-0.008** -0.003	-0.007** -0.003
Creative **×** ***Entre*** **(indicator)**					0.270** 0.119	0.291*** 0.104	0.315*** 0.087	0.315*** 0.086
Part-time (indicator)	-0.828*** 0.009	-0.828*** 0.009	-0.825*** 0.009	-0.826*** 0.009	-0.828*** 0.009	-0.828*** 0.009	-0.825*** 0.009	-0.826*** 0.009
Large city (indicator)	-0.019*** 0.004	-0.020*** 0.004	-0.020*** 0.004	-0.020*** 0.004	-0.020*** 0.004	-0.020*** 0.004	-0.020*** 0.004	-0.020*** 0.004
Medium city (indicator)	-0.001 0.003	-0.001 0.003	-0.001 0.003	-0.001 0.003	-0.001 0.003	-0.001 0.003	-0.001 0.003	-0.001 0.003
Firm size (log)		0.025*** 0.001	0.025*** 0.001	0.025*** 0.001		0.025*** 0.001	0.026*** 0.001	0.026*** 0.001
Job inflow rate to firm (log)			-0.152*** 0.004	-0.152*** 0.004			-0.152*** 0.004	-0.152*** 0.004
Share of creative occupations in firm (log)				-0.013*** 0.004				-0.013*** 0.004
No. of observations	1,792,313	1,792,313	1,792,313	1,792,313	1,792,313	1,792,313	1,792,313	1,792,313
Industry dummies	✓	✓	✓	✓	✓	✓	✓	✓
Combined effect ***Creative*** **and** ***Entre***					0.265** 0.119	0.271*** 0.104	0.307*** 0.086	0.308*** 0.086
R-square	0.122	0.125	0.127	0.127	0.123	0.125	0.127	0.127
PANEL B: Job Mobility from and to Non-Creative Occupations								
Non-Creative **(indicator)**	-0.084*** 0.001	-0.096*** 0.001	-0.066*** 0.001	-0.067*** 0.001	-0.084*** 0.001	-0.096*** 0.001	-0.066*** 0.001	-0.067*** 0.001
Non-Creative **×** ***Entre*** **(indicator)**					-0.033 0.137	0.023 0.136	0.048 0.135	0.050 0.135
Part-time (indicator)	-0.819*** 0.007	-0.829*** 0.007	-0.824*** 0.007	-0.822*** 0.007	-0.819*** 0.006	-0.829*** 0.007	-0.824*** 0.007	-0.822*** 0.007
Large city (indicator)	0.015*** 0.004	0.013*** 0.004	0.013*** 0.004	0.013*** 0.004	0.015*** 0.004	0.014*** 0.004	0.013*** 0.004	0.013*** 0.004
Medium city (indicator)	0.010*** 0.003	0.010*** 0.003	0.010*** 0.003	0.010*** 0.003	0.010*** 0.003	0.010*** 0.003	0.010*** 0.003	0.010*** 0.003
Firm size (log)		0.027*** 0.0006	0.026*** 0.0006	0.0252*** 0.000614		0.027*** 0.0006	0.026*** 0.0006	0.025*** 0.0006
Job inflow rate to firm (log)			-0.118*** 0.002	-0.116*** 0.002			-0.118*** 0.002	-0.116*** 0.002
Share of creative occupations in firm (log)				0.048*** 0.003				0.048*** 0.003
No. of observations	2,814,727	2,814,727	2,814,727	2,814,727	2,814,727	2,814,727	2,814,727	2,814,727
Industry dummies	✓	✓	✓	✓	✓	✓	✓	✓
Combined effect ***Non-Creative*** **and** ***Entre***					-0.116 0.137	-0.074 0.136	-0.018 0.135	-0.017 0.135
R-square	0.105	0.109	0.112	0.112	0.105	0.109	0.112	0.112

Notes: In each cell, the first value is the point estimate and the second value is the robust standard error. Significance levels: * - 10 percent; ** - 5 percent; *** - 1 percent. DiD: Difference-in-Difference model with two-way fixed effects.

5.2 Robustness tests – educational attainment and selection bias

A possible caveat with respect to the results in Table 2 could be that educational attainments confound the results, even if we restrict event histories to exclude changes in education levels for treatment and comparison groups. Furthermore, selection processes into creative occupations may be different from those into non-creative occupations and to control for such non-random job mobility determinants, we include results based on a doubly robust conditional difference-in-difference (CDiD) estimator. Finally, firm contexts in terms of growth paths and knowledge content may confound results, if such contexts affect the likelihood of job mobility into different occupations. Table 3 provides evidence on these concerns. Columns (1) to (3) of Table 3 offer insights into the heterogeneity of effects across education groups based on the FEM estimator incorporating individual-, and time-fixed effects (DiD), while Columns (4) to (6) presents results based on the doubly robust CDiD estimation with three-way fixed effects (individual, time and industry level) to provide evidence on the second concern on selection bias. Furthermore, controls are included for firm growth paths and creative content.

The unconditional earnings effects of job mobility into creative occupations (*Creative*), which are again generally negative in Panel A of Table 3. It may be noticed that the unconditional effects are markedly higher for the CDiD estimator. For instance, while highly educated individuals that change jobs to a creative occupation face a reduction in earnings of 12 percent according to the standard DiD estimator (Column (2)), the same results for the CDiD estimator is about 19 percent (Column (5)). If anything, self-selection, therefore, seems to bias results downwards and lead to more conservative conclusions.

Most importantly, considering the effects of job mobility into creative occupations conditional on entrepreneurial experience (*Creative* × *Entre)*, the effects are similar to Table 2 significantly positive and sizeable for all model specifications. The largest effects are found for the group of low-/medium-skilled individuals. This may arguably indicates some substitution effects between formal education attainments and entrepreneurial experience in earnings.

Entrepreneurial experience increases earnings in Column (2) of Table 3 with 19 percent (*Creative* × *Entre*), but the increase is more than twice as high in Column (3) of Table 3. This pattern is robust to the different estimators applied, as similar findings are shown for the CDiD estimation in Columns (5) with (6) of Table 3.

The results for job mobility into non-creative occupations in Panel B of Table 3 are qualitatively unchanged compared to Panel B of Table 2. As such, the results in Table 2 and 3 appear to be robustness to possible confounding factors in terms of formal educational attainment and in terms of distinguishing between likelihood of treatment and effect of treatment of a conditional difference-in-difference estimator.

A final aspect of importance is possible confounding effects from different firm contexts. To check the robustness of our results to such contexts, we have introduced two measures on firm growth paths and creative content in both Table 2 and Table 3. If individuals from the treatment group with entrepreneurial experience are more likely to switch to firms with high shares of employees in creative occupations, this would bias our results on entrepreneurial experience related to job mobility into creative occupations. To control for this, we include the share of employees in the firm that are in creative occupations. Revisiting Table 2 and Table 3, we see that all the previously discussed results for particularly the importance of entrepreneurial experience in job mobility to creative occupations (*Creative* × *Entre*) hold and are thus robust to the inclusion of controls for creative environments at firm levels. We do accordingly not trace effects from such biases.

Table 3: Earnings effects of job changes by education levels and entrepreneurial experience

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent variable (in logs):	Earnings	Earnings	Earnings	Earnings	Earnings	Earnings
Estimation:	DiD	DiD	DiD	CDiD	CDiD	CDiD

Level of Education:	All	High	Medium and low	All	High	Medium and low
PANEL A: Job Mobility into Creative Occupations						
***Creative* (indicator)**	-0.007** 0.003	-0.120*** 0.005	-0.043*** 0.005	-0.162*** 0.004	-0.192*** 0.005	-0.163*** 0.005
***Creative* × *Entre* (indicator)**	0.315*** 0.086	0.190*** 0.008	0.572*** 0.005	0.374*** 0.120	0.187*** 0.013	0.685*** 0.006
Part-time (indicator)	-0.826*** 0.009	-1.179*** 0.021	-0.708*** 0.009	-1.134*** 0.014	-1.280*** 0.022	-0.989*** 0.018
Large city (indicator)	-0.020*** 0.004	-0.094*** 0.011	0.015*** 0.004	-0.052*** 0.009	-0.087*** 0.012	0.019 0.012
Medium city (indicator)	-0.001 0.003	-0.030*** 0.010	0.002 0.003	-0.020*** 0.008	-0.033*** 0.012	-0.008 0.010
Firm size (log)	0.026*** 0.001	0.013*** 0.002	0.035*** 0.002	0.019*** 0.001	0.012*** 0.002	0.028*** 0.002
Job inflow rate to firm (log)	-0.152*** 0.004	-0.132*** 0.008	-0.110*** 0.004	-0.153*** 0.006	-0.086*** 0.009	-0.201*** 0.010
Share of creative occupations in firm (log)	-0.013*** 0.004	-0.012 0.009	0.003 0.004	0.002 0.006	-0.005 0.009	0.026*** 0.009
No. of observations	1,792,313	232,614	1,559,699	1,705,174	224,106	1,481,068
Industry dummies	✓	✓	✓	✓	✓	✓
Combined effect *Creative* and *Entre*	0.308*** 0.086	0.071*** 0.008	0.529*** 0.002	0.212* 0.120	-0.005 0.012	0.522*** 0.003
R-square	0.127	0.199	0.113	0.192	0.219	0.171
PANEL B: Job Mobility from and to Non-Creative Occupations						
***Non-Creative* (indicator)**	-0.067*** 0.001	-0.034*** 0.006	-0.070*** 0.001	-0.115*** 0.002	-0.088*** 0.007	-0.117*** 0.002
***Non-Creative* × *Entre* (indicator)**	0.050 0.135	0.067 0.216	0.005 0.169	0.052 0.135	0.075 0.216	0.005 0.169
Part-time (indicator)	-0.822*** 0.007	-0.736*** 0.024	-0.827*** 0.007	-0.885*** 0.008	-0.812*** 0.029	-0.889*** 0.008
Large city (indicator)	0.013*** 0.004	-0.091*** 0.013	0.026*** 0.004	0.013*** 0.005	-0.100*** 0.018	0.026*** 0.005
Medium city (indicator)	0.010*** 0.003	-0.008 0.012	0.010*** 0.003	0.010*** 0.004	-0.007 0.015	0.010*** 0.004
Firm size (log)	0.025*** 0.0006	0.017*** 0.003	0.026*** 0.0006	0.025*** 0.0006	0.016*** 0.003	0.025*** 0.0006
Job inflow rate to firm (log)	-0.116*** 0.002	-0.110*** 0.008	-0.116*** 0.002	-0.096*** 0.002	-0.085*** 0.009	-0.097*** 0.002
Share of creative occupations in firm (log)	0.048*** 0.003	0.033*** 0.012	0.052*** 0.003	0.052*** 0.004	0.031** 0.016	0.056*** 0.004
No. of observations	2,814,727	186,913	2,627,814	2,727,588	178,405	2,549,183
Industry dummies	✓	✓	✓	✓	✓	✓
Combined effect *Non-Creative* and *Entre*	-0.017 0.135	0.033 0.216	-0.065 0.169	-0.063 0.135	-0.013 0.216	-0.112 0.169
R-square	0.112	0.131	0.112	0.121	0.135	0.121

Notes: In each cell, the first value is the point estimate and the second value is the robust standard error. Significance levels: * - 10 percent; ** - 5 percent; *** - 1 percent. DiD: Difference-in-Difference model with two-way fixed effects; CDiD: Doubly robust conditional Difference-in-Difference model with two-way fixed effects.

Another concern on biases from firm contexts is that firms with strong growth path have stronger earnings developments, while others are stagnant or receding businesses with weaker earnings. If individuals with entrepreneurial experience are more likely to change jobs to such strong growth firms, this would bias our results on the importance of entrepreneurial experience for job mobility into creative occupations. To control for this, we introduce a job inflow rate at the firm level measuring the number of newly employed individuals for a given year in the firm relative to the total employment. As for the inclusion of this job inflow rate, results remain robust.

This section points to the pivotal role that entrepreneurial experience for the earnings effects of job changes into creative occupations. Job mobility between firms in general triggers a negative earnings effect, but this is more than compensated by positive effects of entrepreneurial experience in creative occupations. Individuals with entrepreneurial experience see a comparably large earnings effect associated with job mobility into creative occupations, while there is no significant effect of entrepreneurial experience for job changes from and to non-creative occupations. Underlying first-stage results on the factors determining individual job changes together with tests for the matching quality of the propensity score-based conditional DiD estimation are given in Appendix B.

6. Discussion and Conclusion

In this work, we have focused on the link between job mobility into creative occupations and individual earnings and have investigated the extent to which prior entrepreneurial experience matters for this link. Our underlying hypothesis was that entrepreneurial experience constitutes a particular type of human capital in the link from creative occupations to earnings. Our empirical findings support this hypothesis. While we find no unconditional earnings effect associated with job mobility into creative occupations, the effect conditional on entrepreneurial experience is significantly positive. Or in quantitative terms: Whereas job mobility generally renders a small negative earnings effect of up to 2 percent, the effect of entrepreneurial experience sizeable outweighs this with a relative earnings increase of 27 percent.

When we account for differences in education levels across individuals, we further find that the earnings increase from job mobility into creative occupations is the largest for low-/medium-skilled individuals. Again this effect significantly depends on the individual's prior entrepreneurial experience. Taken together, entrepreneurial experience is accordingly found to be of particular importance when changing jobs between firms from a non-creative to a creative occupation. In comparison, job mobility between non-creative occupations (controlling for education levels) does not benefit from entrepreneurial experience. The particular value of entrepreneurship as a precursor for gaining entrepreneurial experiences is found in a post-entrepreneurial labor market situation, where such entrepreneurial experience adds to the ability to increase individual earnings and thus create values in creative occupations.

At the same time, the related literature suggests that contextual conditions may be important in terms of human capital and knowledge spillovers. We test if such contexts at the firm level are important, which may confound our results. To control for this, we add two contextual controls at the firm level, specifically the share of individuals in creative occupations out of total employment and the job inflow rate at firm level. The first indicates the possibility of scale effects in creative environments, while the later captures firm heterogeneity in terms of growth paths. The results on the importance of entrepreneurial experience for earnings effects associated with job changes into creative occupations are robust to the inclusion of such contextual controls. Our results, therefore, more generally point to the advantages of gaining the particular type of human capital associated with entrepreneurship in pursuing dependent work with characteristics associated with creative occupations and likely improving on firm innovativeness. We therefore arguably point to some of the underlying mechanisms of the findings in Luzzi and Sasson (2016) that entrepreneurial experience is more valuable in highly innovative environments. If entrepreneurial experience is required in creative occupations as a type of human capital that fosters innovation, then our results are consistent with the results of Luzzi and Sasson (2016).

It is noticeable that our approach is different from previous contributions. The focus is here on how individual earnings increase from job mobility into creative occupations conditional on having entrepreneurial experience. Åstebro and Yong (2016) argue for the importance of specific mixes of occupational variety and industry variety in jobs prior to entrepreneurship for the invention quality by entrepreneurs, which shows the importance of prior job experiences for successful entrepreneurship. Laffineur et al. (2020) point to three different occupational characteristics triggering entrepreneurial effort. From an entrepreneurial career perspective, we move one step forwards asking about the post-entrepreneurial importance of entrepreneurial experience for occupations with specific characteristics. Still, it points to the importance of considering the skills and human capital generated throughout entrepreneurial careers in more detail.

Both the contributions by Luzzi and Sasson (2016) and Åstebro and Yong (2016) point to links between entrepreneurship, innovativeness and invention quality. One may reflect upon the link from job mobility into creative occupations by an individual with entrepreneurial experience on the subsequent innovativeness of firms. This is beyond the scope of the current analysis and available data but would be a natural next step in terms of future research. At present, we offer evidence on the positive effects of entrepreneurial experience in enhancing the individual job performance (measured through earnings) and thus adding value in creative occupations.

Kaiser and Malchow-Møller (2011) find that entrepreneurial experience has a negative effect on earnings compared to those that did not have such experience. This negative effect does though for some specifications become positive if the dependent employment is in the same sector as the sector in which entrepreneurial experience was gained. Our focus on job mobility into creative and non-creative occupations offers a different insight: While we control for sectoral association in the post entrepreneurial dependent job including industry dummies in all specifications, we find that positive effects are associated with creative occupations in which dependent work is gained after entrepreneurship. This relates less to sectoral matching prior and post to dependent work, but more to these types of occupations and the particular type of human capital gained through entrepreneurship is particularly valuable for firms. To the extent that such occupations map to the hierarchy of occupations and earnings in forms, the results provides additional insights into the entry and promotion dynamics pointed out in Baptista et al. (2012) and the evidence on earnings quantiles from Failla et al. (2017).

Finally, our analysis uses rather aggregate definitions of creative and non-creative occupations. One may consider this as *ad hoc* and a drawback given that creative tasks may have many natures. This is, for instance, reflected in the different types of occupations included in different subcategories of the creative class as shown in Table A1 (Appendix A) following Boschma and Fritsch (2009). One may consider diving into such a more diverse and multi-dimensional analysis, but this could lead to a curse of dimensionality arguing that one should rather go to specific occupation types at e.g. three-digit levels of the ISCO classification. We notice that this would in principle be possible with our register data set. A restriction is though that we need to observe sufficient number of job moves into creative occupations. With our particular design of identifying treated individuals through job moves, considering lower levels of aggregation will erode the number of observations on which the analysis in a difference-in-difference setup can be undertaken and thereby endangers the robust identification of effects. We, therefore, note that using rather aggregate measures of creative occupations does not dilute effects and still provides very clear conclusions on the importance of entrepreneurial experience for creative occupations in firms. Future research may consider more disaggregated or alternatively defined lists of creative occupations and alternative sets of underlying characteristics of occupations than that of creative occupations. Until such analyses is available, our empirical findings can be taken as valuable insight on the importance of entrepreneurial experience in terms of enhancing job performance and adding value in creative occupations and industries.

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Appendix A: Definitions and Descriptive Statistics

Table A1: List of creative occupations in the concept of the creative class

Creative Core	**Creative professionals**	**Bohemians**
Physicists, chemists, and related professionals (211)	Legislators, senior officials, and managers (1)	Writers and creative or performing artists (245)
Mathematicians, statisticians, and related professionals (212)	Nursing and midwifery professionals (223)	Photographers and image and sound recording equipment operators (3131)
Computing professionals (213)	Business professionals (241)	Artistic, entertainment, and sports associate professionals (347)
Architects, engineers, and related professionals (214)	Legal professionals (242)	Fashion and other models (521)
Life science professionals (221)	Physical and engineering science associate professionals (31)	
Health professionals (except nursing) (222)	Life science and health associate professionals (32)	
College, university, and higher education teaching professionals (231)	Finance and sales associate professionals (341)	
Secondary education teaching professionals (232)	Business services agents and trade brokers (342)	
Primary and pre-primary education teaching professionals (233)	Administrative associate professionals (343)	
Special-education teaching professionals (234)	Police inspectors and detectives (345)	
Other teaching professionals (235)	Social work associate professionals (346)	
Archivists, librarians, and related information professionals (243)		
Social sciences and related professionals (244)		
Public service administrative professionals (247)		

Notes: Creative class definition based on Florida (2005), Boschma and Fritsch (2009) and chosen from Danish database from DST.

Table A2: List of variables used for estimation and variable definitions

Variables	Definitions	Mean	S.D.
Earnings	Annual earnings (in local currency, Danish kroner)	301,865	126,089
Creative	Job change between two firms from non-creative to creative occupation (binary dummy)	0.076	0.266
Non-Creative	Job change between two firms from non-creative to non-creative occupation (binary dummy)	0.412	0.492
Entre	Self-employment experience before entering into the paid employment (binary dummy)	0.146	0.353
Age	Age in years	43.81	10.69
Part-time	Indicator for part-time employment (binary dummy)	0.025	0.157
High education	Long-cycle higher education (approximately 1-2 years at the Masters level and 3-4 years of PhD level; binary dummy)	0.104	0.305
Low and medium education	Short- and medium-cycle education (Primary, high school, professional school education and short high education --approx.: 2 years that leads to the higher education or approx..: 3-4 years and the Bachelors level; binary dummy)	0.896	0.305
Firm Size	Number of employees per firm (in persons)	4,229.34	7,489.81
Share of creative occupations in firm	Share of workers in creative occupations in the firm (number of workers in creative occupations divided by total number of workers in the firm; 100%=1)	0.264	0.211
Job inflow rate	Share of newly recruited employees out of total employment in firm (100%=1)	0.153	0.213

Notes: S.D. = Standard deviation. Data are reported for the full sample from DST. Not reported are binary dummy variables for the following sectoral aggregates: 1. Agriculture, fishing, mining, 2. Manufacturing, 3. Energy and water supply, 4. Building and construction, 5. Trade, hotel, restauration, 6. Transport, post and telecom, 7. Finance and business, 8. Public and personal service. Additionally, the following binary dummies for city types have been used for estimation (see Ministry of Housing, Urban and Rural Affairs, 2013): 1. Large: population of 100,000 and above, 2. Medium: 20,000 to 99,999 population, 3. Small: population 19,999 and below. Details can be obtained from the authors upon request.

Appendix B: Factors Determining Job Mobility into Creative Occupations

This appendix reports the first-stage estimation results of the underlying probability of being selected into the two treatment groups. As Table A3 shows, the probability of a job change into a creative occupation is generally higher for males than for females, while the probability of a job change into a non-creative occupation is lower for males compared to females. On the other hand, age reduces the probability of job mobility in general. This effect is stronger for creative occupations, but the rate of decrease is lower and lower shown by results on the squared value of age. Notice that this does not apply to job mobility from and to non-creative occupations.

The probability of a job change into a creative occupation increases with education levels but decreases with larger firm size. The later also applies to non-creative occupations apart from highly educated. Once arrived at a non-creative job in one firm, highly educated therefore show a stronger persistence in remaining in the non-creative occupations, but on the other hand, has a higher probability of changing to a creative occupation in another firm. Highly educated individuals experiencing an initial match to a non-creative occupation through job search will, therefore, be less active moving among non-creative occupations, but will rather wait for a chance to change into a creative occupation.

What stands out in Table A3 is the effect of a share of creative occupations in the firm. A higher share of creative occupations in the firm increases the probability of a job change into a creative occupation sizably, but only has a limited effect on the probability of a job change to a non-creative occupation. Even so, the share of creative occupations in the firm has significant effects in both instances. To assess the quality of propensity score matching we use a balancing test based on the computation of McFadden R^2 before and after matching (Sianesi, 2004). The idea of this test is that after successful matching, there should be no remaining differences in the distribution of included covariates, i.e. the explanatory power of covariates in the matched sample should be very low.

Table A3: First-step results for probability of job mobility into (non-) creative occupations

	***Pr*(*Creative*)**	***Pr*(*Non-Creative*)**
Earnings (log)	-0.010* 0.006	-0.287*** 0.003
Male (indicator)	0.250*** 0.007	-0.059*** 0.004
Age (log)	-0.029*** 0.002	-0.007*** 0.001
Age-square (log)	0.00002 0.00003	-0.00005*** 0.00001
Part time (indicator)	0.075*** 0.017	-0.336*** 0.009
High education level (indicator)	1.586*** 0.010	-0.095*** 0.007
Medium education level (indicator)	0.118*** 0.009	0.043*** 0.004
Low education level (indicator)	*Reference category*	*Reference category*
Firm size (log)	-0.018*** 0.001	-0.003*** 0.0008
Large city (indicator)	-0.061*** 0.008	-0.379*** 0.004
Medium city (indicator)	0.070*** 0.009	-0.010** 0.005
Small city	*Reference category*	*Reference category*
Share of creative occupations in firm (log)	1.330*** 0.015	0.185*** 0.011
Number of observations	333,710	545,912
Industry dummies	✓	✓
McFadden-R^2 (before matching)	0.280	0.094
McFadden-R^2 (after matching)	0.036	0.030

Notes: In each cell, the first value is the point estimate and the second value is the robust standard error. Significance levels: * - 10 percent; ** - 5 percent; *** - 1 percent.

As Table A3 shows for the case of job changes into creative occupations, the included individual- and firm-specific covariates explain roughly 28 percent of the variance in the probability of switching between firms to a creative occupation before matching. The explanatory power significantly decreases after matching (to less than 4 percent). A similar, though less significant reduction, can also be observed for the case of job changes into non-creative occupations. Although the after-matching explanatory power is not entirely zero, the strong reduction in the McFadden R^2 can be taken as an indicator for the proper functioning of the propensity score matching.