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SHOULD I STAY OR SHOULD I GO? HOW MOBILITY EXPLAINS INDIVIDUAL SCIENTIFIC PERFORMANCE

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Abstract

Management scholars have developed several theories on the use of hiring from other firms as a mean for acquiring knowledge or learning and on the boundary conditions under which spillovers exist and generate effects for the firm's performance. While the relationship between inter-organizational mobility and organizational performance has been extensively studied, significantly less work has been done on the implications of such relationship at the level of the single moving individual. In addition to this theoretical gap, this research area presents also an interesting empirical gap related the simultaneous nature of the individual mobility-performance relationship. In this paper we analyze the relationship between mobility and individual performance using an instrumental variable approach and dynamic panel data modelling. The key finding of this paper is that individuals who move across institutions increase their individual performance. By using the context of academic researchers and scientific productivity, we tried to relax some of the assumptions deriving from specific contextual factors in knowledge-intensive. In particular we make predictions in a context in which knowledge assets represented by the individual human capital are less embedded in the organizational routines, thus, facilitating a stronger ownership and use by each individual of her own human capital.

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ABSTRACT

Management scholars have developed several theories on the use of hiring from other firms as a mean for acquiring knowledge or learning and on the boundary conditions under which spillovers exist and generate effects for the firm's performance. While the relationship between inter-organizational mobility and organizational performance has been extensively studied, significantly less work has been done on the implications of such relationship at the level of the single moving individual. In addition to this theoretical gap, this research area presents also an interesting empirical gap related the simultaneous nature of the individual mobility-performance relationship. In this paper we analyze the relationship between mobility and individual performance using an instrumental variable approach and dynamic panel data modelling. The key finding of this paper is that individuals who move across institutions increase their individual performance. By using the context of academic researchers and scientific productivity, we tried to relax some of the assumptions deriving from specific contextual factors in knowledge-intensive. In particular we make predictions in a context in which knowledge assets represented by the individual human capital are less embedded in the organizational routines, thus, facilitating a stronger ownership and use by each individual of her own human capital.

INTRODUCTION

In knowledge intensive industries human capital is a strategic asset critical for competition (Coff, 1997). According to knowledge-based view, knowledge is embedded in individuals (Grant, 1996) and it is socially combined in routines that generate innovative activities (Kogut & Zander, 1992; Nelson & Winter, 1982). More accurately, the tacit component of knowledge, which is highly embedded in individuals, is precisely one of the key sources of competitive advantage (Coff, 1997; Lippman & Rumelt, 1982). Especially in knowledge-intensive industries, the strategic management of human assets is therefore particularly critical. As individuals can leave their employment, organizations face the possibility not only to lose their competitive advantage, but also to give crucial resources (in the form of human assets) to their competitors. For this reason, strategic management and innovation scholars have paid a lot of attention to the mobility of talented employees and its strategic implications for firm performance (Aime, Johnson, Ridge, & Hill, 2010; Campbell, Ganco, Franco, & Agarwal, 2012b; Corredoira & Rosenkopf, 2010; Somaya, Williamson, & Lorinkova, 2008), focusing mainly on the idea that mobility is an important mechanism to transfer valuable knowledge from one firm to another.

Building on the pioneer works of Arrow's (1962) and Levin et al. (1987) on the link between labor mobility and knowledge spillovers, management scholars have developed several studies on the use of hiring from other firms as a mean for acquiring knowledge or learning (Rosenkopf & Almeida, 2003; Singh & Agrawal, 2011; Song, Almeida, & Wu, 2003) and on the boundary conditions under which spillovers exist and generate effects for the firm's performance (Agarwal, Ganco, & Ziedonis, 2009; Agrawal, Cockburn, & McHale, 2006; Corredoira & Rosenkopf, 2010). While the relationship between inter-organizational mobility and

organizational performance has been extensively studied, significantly less work has been done on the implications of such relationship at the level of the single moving individual. In particular, this research focuses either (and mainly) on the effect of individual performance on the likelihood of inter-organizational mobility (Campbell et al., 2012b; Carnahan, Agarwal, & Campbell, 2012; Palomeras & Melero, 2010) or (and less) on the effect of inter-organizational mobility on individual productivity (Groysberg, Lee, & Nanda, 2008). Looking at the individual productivity implications is very important to assess more precisely the effect of learning across firms. In fact, Rosenkopf and Almeida (2003) suggest that firms learn from each other using hiring as a mechanisms to transfer knowledge via moving individuals. But, when Singh and Agrawal (2011) re-test this theory using a more sophisticated research design, they find that this learning effect is significantly reduced after considering the self-citations of the moving inventors after the move, suggesting that the “learning by hiring” could be in fact “exploiting by hiring”. Recent research on mobility is therefore questioning the actual value of performance implications of mobility of talented employees. This is why we believe that looking at the individual performance implication of the moving inventors represent a step further in the direction of better understanding the underlying mechanisms and the assumption behind the phenomenon of inter-organizational mobility.

In addition to this theoretical gap, this research area presents also an interesting and still debated empirical gap related the simultaneous nature of the individual mobility-performance relationship. In a recent contribution, Hoisl (2007) offers an attempt to deal with such simultaneity. The scenario emerging from this research empirical results is however puzzling. First, it is still not clear empirically whether individual productivity has a positive or negative relationship with inter-organizational mobility. On the one hand, Hoisl (2007) suggests that

movers are more productive than non-movers, but at the same time increases in productivity decrease the likelihood of mobility. On the other hand, Palomeras and Melero (2010) find that these results depend on the type of innovative performance measure considered. Looking at IBM inventors during the 90s, they show that increased individual patenting performance (i.e. quantity of innovation) is negatively related to mobility as in Hoisl (2007), but more citations to the individual's patents (i.e. quality of innovation) are positively related to a higher likelihood of mobility. Second, it is not clear yet whether inter-organizational mobility increases or decreases the individual productivity of the moving employee. Also in this case, evidence is mixed. While some studies suggest that moving individuals are more productive after the move (Hoisl, 2007), others find no significant effect (Fernández-Zubieta, Geuna, & Lawson, 2013) or suggest the opposite result (i.e. decreasing performance after mobility) questioning the portability of the competitive advantage generate by talented human capital (Groysberg et al., 2008; Wezel, Cattani, & Pennings, 2006). Understanding the nature of the relationship between mobility and individual performance is important from the point of view of both employees and organizations. While the organizational implications for the source and recipient firms have been largely overlooked in the study of mobility of talented employees, individuals have a clear interest in understanding how their mobility patterns will affect their performance, which as a reflection of ability will in turn affect their career prospects both on the internal and external labor markets. And, from the point of view of organizations, understanding if hiring highly-skilled workers from other entities is a value-creating or value-destroying proposition is critical in building and maintaining a sustainable competitive advantage (Groysberg et al., 2008).

Building on this rich set of theoretical and empirical contributions, this study proposes to address the question "how does mobility affect individual productivity?". We believe that the

empirical puzzle currently existing in understanding the mobility-performance relationship is mainly due to two main aspects. First, the simultaneous nature of this bi-directional relationship generates strong endogeneity issues related to the empirical strategy adopted in previous studies. In this sense, significant improvements have been proposed to model such endogeneity, such as using control-group design (Groysberg et al., 2008) and instrumental variable techniques (Hoisl, 2007). This endogeneity problem in the mobility-performance relationship has also been recently acknowledged by Singh and Agrawal (2011), where a difference-in-difference empirical strategy is proposed to estimate the citation flows (i.e. measure of performance) between source and recipients firm before and after mobility events. The authors observe, though, that “mobility is endogenous, not random; firms make deliberate choices about who to recruit for a reason” (pp.147), inviting future researchers interested in the mobility-performance relationship to address more systematically this causality issue. Moreover, the dynamic nature of individual performance over time has been less considered, especially when taking into account not only the simultaneity of this relationship of interest, but also that performance is determined by previous performance levels, severely challenging the hypothesis of independence of the individual’s performance levels over time. While appropriate econometric techniques are available to take into account the dynamic nature of individuals’ productivity, their implementation requires detailed longitudinal data on the activities of employees, information that is often difficult to collect.

Second, most researchers test their hypotheses in empirical contexts where specific environmental and organizational factors play a fundamental role in shaping not only the relationship between performance and mobility, but also the related portability of the competitive advantage generated by talented human capital. We think that the assumptions deriving from the

choice of the context of analysis play a major and non-negligible role in shaping the results we have had so far in the literature, ultimately limiting their generalizability to other settings. In this sense, several contextual factors in knowledge-intensive industries (for example semiconductors or pharmaceuticals) which are usually subject of empirical research on mobility constitute a potential source of bias in the analysis.

To begin with, it is still very difficult to objectively measure the performance of knowledge workers (Ernst & Vitt, 2000). The high causal ambiguity between input and output in the value creation process means that on average current employer are better than any other possible future employer in observing the value of the human capital embedded in each individual. This means that the job market for highly-skilled individuals in knowledge-intensive industries is characterized by high asymmetric information (Chiang & Chiang, 1990; Jovanovic, 1979). Under these conditions, the contracts and the related incentives offered by the source are better than any other source, making mobility a potentially risky strategy for employees.

Asymmetric information, however, is not the only feature that structurally affects mobility in knowledge-intensive industries. Using human capital as a source of competitive advantage is possible only if employees' skills are not easily mobile or transferable across firms (Barney, 1991). This means that firms should promote the development of firm-specific human capital, which is valuable only to a specific organization, over general human capital, which is applicable to many different organizational contexts (Becker, 1962; Campbell, Coff, & Kruscynski, 2012a). Organizations can make employees very much firm-specific in their human capital, lowering the value of employment in other possible recipient organizations. In knowledge-intensive industries, the popular belief has long been that employees talent is highly portable and that therefore workers' performance rely almost entirely on general human capital (Felin & Hesterly,

2007). More recent studies, however, have highlighted the crucial role of firm-specific human capital in knowledge-based work (Baks, 2003; Groysberg et al., 2008; Huckman & Pisano, 2006). This inherent “stickiness” of firm-specific human capital has a very important implication for the consequences of mobility on individual performance. If the skills acquired while employed with a specific organization are not easily transportable or applicable to a new organization, then individuals will suffer a performance decline when they move to new employers (Groysberg et al., 2008; Wezel et al., 2006), which in turn affects the overall organizational performance and competitive advantage.

The effort in creating firm-specific human capital is not the only way in which organizations can increase the value of human capital for their competitive advantage. Another way is through formalized clauses included in employment contracts. For example, Marx and colleagues (2009) show the importance of non-disclosure agreements (NDA) in reducing the rate of inter-organizational mobility in regions where they are enforced (i.e. Michigan MARA) compared to regions where they are not. Along this line, NDAs have also been shown to reduce patenting and entrepreneurial initiatives (Png, 2012; Samila & Sorenson, 2011). In fact, Campbell et al. (2012b) show that more capable employees are less likely to move, but when they move they are also more likely to found a new venture rather than joining an incumbent. They argue that more capable employees are more able to appropriate complementary assets, therefore lowering the risks of starting a new venture once they move. On the other hand, this effect may also be the result of selection issues. If NDAs apply disproportionately to the most talented employees, this will make them less attractive to other incumbent organizations, and therefore relatively more likely to start their own ventures once they move.

Our study is an attempt to deal with these two relevant aspects in order to understand the effect of inter-organizational mobility on individual performance. In particular, we aim to offer both a conceptual and an empirical contribution to the literature of mobility of talented employees in knowledge-intensive industries

Conceptually, we aim at relaxing some of the structural constraints mentioned, which characterize the job markets most commonly analyzed, which we believe strongly influence the results obtained in the literature so far. In order to do so, we examine a different category of knowledge workers, namely academic faculty members. We believe the academic context is particularly suitable to observe a “cleaner” effect of inter-organizational mobility on individual performance because this setting does not present the same (constraining) structural features of the other knowledge-intensive industries analyzed so far. First of all, the university context allows observing meaningful and quantifiable knowledge production outcomes over time. While publications are not perfect carriers of information (Lissoni, Montobbio, & Zirulia, 2013), they are undoubtedly the main measure of individual performance in academia. Moreover, publications in peer-refereed journals can be evaluated following widely accepted and objective measures, such as the number of citations received or the impact factor of the journal where the publication appears. This feature drastically reduces the causal ambiguity between input and output that we observe in the context of other knowledge-intensive industries.

Second, one of the most salient characteristics of the university environment is the autonomy which is granted to researchers. Indeed, the defining characteristic of academic research is that individual scientists value creative control (Aghion, Dewatripont, & Stein, 2008) and that they retain decision rights over the projects they take on and the methods they use to tackle them. While scientists do not work in isolation, and many contributions have highlighted the

importance of collaboration for scientific production (Adams, Black, Clemmons, & Stephan, 2005; Boudreau, Ganguli, Gaule, Guinan, & Lakhani, 2012; Catalini, 2012; Stephan & Levin, 1997), academics are not bound to a specific organization as the nature of scientific research in academia makes them possess human capital which is highly general, and therefore easily transportable between different universities.

Finally, in the specific national context we use in this study (the United Kingdom), academic researchers face a very fluid labor market, where mobility barriers are very low and mobility is usually rewarded. Several features contribute to this fluidity. First, the absence of a tenure system: once in a faculty position, individuals have a three-year' probation period, after which the contract is made permanent. This implies that the effect of the possible bias introduced by mechanisms confounding voluntary and involuntary mobility (ex. tenure system) is significantly less relevant. Second, when researchers win funding through competitive sources as principal investigators (for example grants awarded by the Research Councils) they are free to take the grant with them to a new institution if they move. Because resources are essential to perform cutting-edge research (especially in natural and physical sciences, where researchers need expensive equipment and large laboratories), they clearly give a competitive advantage to those academics who possess them. And as resources are portable, this means that in this context it is realistic to assume portability of individuals' competitive advantage. Third, academic salaries tend to vary within a well-defined national range (based on experience), with more flexibility at the top of the career ladder (i.e. full professorship positions).

In addition to this conceptual contribution, this study advances the methodology employed in previous empirical research on mobility and individual performance in two significant ways. First, recognizing the inherent issue of simultaneity of mobility and performance (Hoisl, 2007;

Singh & Agrawal, 2011), we estimate our main model using instrumental variables. Second, in order to address the dynamic nature of the data, we employ Arellano – Bond Dynamic Panel GMM Estimators.

The remainder of the paper is organized as follows. In Section 2, we describe the context of our study and the construction of the dataset we use. In section 3, we outline our empirical framework and we distinguish it from the approaches used in the literature so far. In section 4, we present our empirical results. Finally, in section 5, we discuss the implications of our findings, the limitations of our study, and potential avenues for future research.

CONTEXT AND SAMPLE

UK academic system

The United Kingdom presents an advanced scientific system, making the country an elite performer in science. In 2008, researchers in the UK published 76683 scientific articles, the third highest performance in the OECD area after the United States and Japan (OECD, 2010).

Historically the UK university system was dominated by the so-called Ancient Universities (such as Cambridge and Oxford) created between the 12th and 16th century, the University of London (19th century) and the Red Brick Universities, created before the First World War in large industrial cities such as Sheffield and Birmingham. Changes began in 1963 when the Robbins Report recommended that education enrolment should be increased in order to meet the needs of the economy (Robbins, 1963), and as a consequence new universities were built on campuses designated outside towns and cities. Finally, in 1992, a group of former polytechnics and colleges of higher education were given university status by John Major's government.

Universities in the UK are characterized by a high degree of autonomy in terms of budget, recruitment and choices of curricula. The funding regime of UK universities makes the academic system extremely competitive and entrepreneurial. Central government funding for science and research activities in universities flows through three main routes. The first (and most important) is represented by the so-called Dual Support system, which is composed by a block grant funding for Higher Education Institutions, complemented by project funding. The block grant funding is administered by the Higher Education Funding Council for England (HEFCE) (and analogous bodies in Wales, Scotland and Northern Ireland): it is quality based and it is allocated based on the periodic assessment of British Universities (the Research Assessment Exercise, now called Research Excellence Framework). This funding provides resources for basic research infrastructure and permanent staff salaries: ideally it provides institutions with the flexibility to react quickly to new areas of investigation and to perform 'blue skies' research. This funding is however of limited entity (especially if compared with project funding) and permanent staff salaries are mainly funded through the money the government distributes to higher education institutions for teaching activities (in 2013-14 HEFCE will distribute £2.3 billion to support learning and teaching in universities and colleges).

The project funding comes from specific programmes (responsive mode) of the seven Research Councils through grants to individual academics and departments: proposals are evaluated by peer review and the allocation decision follows a strategic direction. In 2010, HEFCE distributed £ 1.73 billion as block grant funding, while the Research Councils awarded grants for £ 2.6 billion (HEFCE, 2011). Other public organizations (such as the NHS), foundations and firms also provide funds to British universities. For example, in 1998 the Wellcome Trust has established a partnership with the UK government to fund world-class

biomedical research in the country. Unlike other academic systems in Europe, researchers are often required to acquire external resources through competition.

The second route is a dedicated capital funding through the Science Research Investment Fund. The third route is the Knowledge Transfer funding, currently distributed by the Higher Education Innovation Fund (HEIF). Funding includes support for a range of commercial activities, including academics' commercial ventures, personnel exchanges between university and industry, and university patenting; however, the majority of these funds have been used to build up and extend the efforts of university TTOs (Mustar & Wright, 2010).

Data

The study is based on a sample of 80 research active academics working in life science departments of UK universities from 1995 to 2007. The dataset used in this study is a subset of a larger dataset containing information on a random sample of researchers who were awarded at least one grant from the Biotechnology and Biological Sciences Research Council (BBSRC) since 1997. The BBSRC was created in 1994 and it is nowadays the largest UK public funder of non-medical bioscience: in 2012, it disbursed £200M for bioscience. The EPSRC encourages partnerships between researchers and third parties, such as private firms, public bodies, non-profit organizations etc. However, there is no requirement for most research projects to have an industrial partner. The selection of projects is based solely on peer review.

The names of the researchers have been randomly selected from the list of all grants awarded by the BBSRC and their CVs have been collected on their personal webpages. Career information taken from CVs was coded in order to construct comprehensive profiles of the researchers, including their education history, employment history and publications, resulting in a panel dataset spanning from 1970 to 2010. CV data have been widely used in the economics of

science literature as they provide very reliable information both on job changes and personal publication records (Cañibano & Bozeman, 2009).

From the full dataset, we first excluded all researchers with a hybrid career, i.e. who had been employed both in academia and in industry. Because our measure of individual performance is based on the number of articles published, we wanted to make sure that researchers were faced with similar incentives to publish along their career. While it is common for industrial researchers to publish in peer-reviewed journals and many firms use publications as a signal of the quality of the research their employees perform, industrial research mainly follows a commercial logic. While one of the pillars of the academic logic is the academics' willingness to disseminate research results as widely as possible (Dasgupta & David, 1994), commercial firms seek protection of their findings through secrecy and other intellectual property rights, in an attempt to profit from the knowledge they produce (Cohen, Nelson, & Walsh, 2000), thus limiting in many cases the possibilities for publication for their employees. Additionally, we excluded researchers with a purely academic career who moved across different countries. This was done in order to have a population facing similar macro-level issues during their career.

All universities in the dataset have been manually matched with their unique code (HESA code) assigned by the Higher Education Statistics Agency. The code has then been matched with data on students' number, income and research quality.

EMPIRICAL STRATEGY

Variables

Our dependent variable is Scientific Productivity. This variable is defined as the count of scientific publication published by each individual in every year. One of the main goals of

scientists is to establish priority of discovery (Merton, 1957) because the reward to priority is the recognition awarded by the scientific community for being first. A necessary step in establishing priority is undoubtedly publication (Stephan, 1996): therefore it has become common practice to measure scientific productivity in terms of number of articles published by a researcher.

Figure 1 shows the distribution of individual scientific productivity. We divide the productivity per year (i.e. count of publications per year) in 6 categories. In general, we notice that the distribution is skewed, as expected; so, 30% of the individuals (24) have published less than one article per year, and they represent the highest share of the sample. 19% of the academic scientists in our sample (15) produce more than 5 publications per year and account for approximately 54% of the total publications in the sample (2,984) with an average of 11.6 years of observation out of 13. This skewed distribution is a common feature of scientific production, and was first observed by Alfred Lotka in a study of 19th century physics journals (Lotka, 1926). Lotka's law has since been found to fit data from several periods of time and scientific disciplines (de Solla Price, 1986; Stephan, 1996).

Add Figure 1

Our independent variable is Mobility. For each individual in our sample we track her carrier and affiliation in each period of observation. If an individual spends her entire carrier in the institution in which she found employment after the doctoral studies (i.e. first employer), we

code our variable as 0 for the entire individual time series¹. If an individual changes affiliation once during her time series, we code each individual-year observation in the new employer as 1. If an individual changes a second time affiliation during her time series, we code each individual-year observation in the second new employer as 2. A similar logic is applied for any further change in the individual affiliation. So, Mobility is the number of moves per each individual tracked over the period of observation. Figure 2 reports the distribution of the number of moves per individual. In general the distribution of frequency of moves is right skewed (i.e. more individuals for either zero or low number of moves). In our sample, 74% of the scientists move at least once (59), and the mode of the distribution is 1 (45% of the sample, which stands for 36 individuals). In fact, 66% of the sample moves either 1 or 2 times. Overall, the rate of mobility within our sample is quite high.

Add Figure 2

Identification strategy

Our empirical analysis is primarily aimed at estimating the causal effect of academic mobility on individual productivity. Our empirical model is based on the following equation:

$$y_{it} = X_{it}\beta + \alpha_i + u_{it}$$

¹ Post-doctoral positions are considered as doctoral studies, so they are not included in the time series and, thus, do not contribute as employment periods for the codification of inter-organizational mobility.

where y_{it} is the Scientific Productivity for each individual i in each period t , X_{it} is the mobility status (i.e. Mobility) for each individual i in each period t , β is the coefficient of X on y , α_i is the unobserved time-invariant individual effect for each individual i , and u_{it} the error term.

As mentioned in Section 1, this empirical model suffers from two sources of bias. First, as observed in previous research (Groysberg et al., 2008; Hoisl, 2007; Singh & Agrawal, 2011), we expect the relationship between productivity and inter-organizational mobility to be endogenous. There are two separate aspects that underlie such endogeneity. One aspect refers to the simultaneity inherent in this relationship: individual performance and individual inter-organizational mobility are indeed simultaneously determined (Hoisl, 2007). The other aspect is an omitted-variable bias related to mobility. Fixed-effects (FE) methods would allow us to model the part of variance of the scientific productivity explained by unobserved characteristics both of the individual and of the employer. But, there might also be unobservable factors at the level of the labor market for academics that affect both the opportunity and propensity to move of each individual and their individual performance.

In order to deal with this endogeneity issue, our identification strategy rests on the use of an instrumental variable (IV). IV estimation can be applied for simultaneous or causal relationships if it is possible to argue that some regressors determine the independent variable (mobility, in our case) but not the dependent variable (individual performance, in our case). This strategy allows a consistent estimation of the performance equation. More precisely, we use the number of students enrolled at the university of affiliation of the researcher (Students Enrolled) as an instrumental variable. As discussed in Section 2, the government (through HEFCE) allocates universities funding for teaching-related activities based on the number of students enrolled. Among other uses (such as financing grants for students), this money is used to open permanent

faculty positions. These openings affect the academic labor market, influencing in turn individual researchers' mobility. Thus, we expect a positive relationship between the Students Enrolled and Mobility. Contrary to the relevance of the instrument, its exogeneity cannot be tested empirically. However, we can exclude quite confidently a direct effect of the number of students of the individual scientific performance. While an increase in the number of students increases the resources a university can dispose of, these resources cannot be used to fund research projects. As discussed in Section 2, research in UK universities is mainly financed through the Dual Support system, and funds for teaching and research are administered and kept separate.

Second, the level of individual performance in every period also depends on the level of performance in the previous period. Introducing in the specification the lagged individual performance level raises issues of autocorrelation in our FE model (included in the instrumental variable identification) that would bias our results, implying, thus, the need of a dynamic panel-data (DPD) model as an additional identification strategy.

Therefore, taking into account the DPD nature of our data in addition to the presence of an omitted-variable bias, our final identification strategy is based on the approach of Arellano and Bond (1991). The Arellano-Bond approach is especially suited for our empirical setting as its estimator is designed for situations with: (a) "small T, large N" panels; (b) linear functional relationships; (c) a dependent variable which depends on its own past realizations; (d) non strictly exogenous independent variables; (e) fixed individual effects; (f) heteroskedasticity and autocorrelation within, but not across, individuals. The estimations transforms regressors by first differencing and uses the Generalized Method of Moments (Hansen, 1982). The main idea is to take first differences to get rid of the individual effects and then use all past information of the dependent variable as instruments. Finally, as we do not expect high persistence in our series and

we do not want to increase too much the number of instruments as we have a low number of observations, we decide to employ the difference GMM estimation.

RESULTS

Our main results are reported in Table 1, which shows the models predicting the effect of Mobility on Scientific Productivity. While Table 1 presents several models, Model 5 and Model 6 are our preferred specifications because of the identification concerns presented in the previous section. However, for a general interpretation of the result, we focus on Model 6 because it does show a better fit to the data compared to Model 5. For models identified using an instrumental variable approach (models 3, 4, 5 and 6), Table 1 reports only the second stage results. Estimates of the first stage of Model 3 and Model 4 are reported in Appendix 1, which shows a positive and significant relationship between Students Enrolled and Mobility, as argued above to be expected in our sample.

Model 1 and Model 2 are specified using Ordinary Least Squares (OLS), respectively with fixed effects (FE) and random effects (RE) but without IV identification². Model 3 and Model 4 are OLS models respectively with fixed-effects (FE) and random-effects (RE) identified using an IV approach³; Model 5 and Model 6 are the Arellano-Bond GMM specifications⁴. All the

² RE model provides not significant statistics of its goodness of fit and the coefficient of Mobility is not significantly different than 0. The FE model shows a fairly good fit statistics (significant at 5% level); the coefficient of Mobility in this model is positive and significant at 5% level. So, in general, the results without modeling endogeneity show weak fit to the data or not significant results, suggesting that our IV empirical strategy might be an appropriate design.

³ We believe that the unobserved time-invariant characteristics of the individual correlate with our main independent variable, Mobility. For this reason, we believe a FE model is more appropriate give our research question and sample characteristics. We run both FE and RE models and the related Hausman test: while holding the same estimates for the effect of Mobility on Scientific Productivity (positive and significant), the test does reject the

estimates of Mobility are positive and significant ($z < 0.05$) across different models (except for Model 2), suggesting that individuals increase their productivity the more moving across employers. So, our predictions are confirmed by our analysis.

Add Table 1

Table 2 offers a more detail analysis of the results of Model 6, our preferred model for the interpretation of our results. The estimates suggest that each further move generates a statistically significant increase of 4.32 publication for the individual moving ($z < 0.01$). Our main motivation behind the Arellano-Bond choice for the empirical strategy is the presence of autocorrelation of the residuals. By construction, the residuals of the differenced equation should possess serial correlation, but if the assumption of serial independence in the original errors is warranted, the differenced residuals should not exhibit significant AR(2) behavior. In fact, the test for first-order serial correlation AR(1) rejects serial correlation in differences ($z = -5.14$), and the test for second-order serial correlation AR(2) does not reject serial correlation in level ($z = 1.01$). Regarding the test of exogeneity of our instruments, the result of the Sargan test suggest that we cannot reject that our group of instruments are exogenous ($\text{Prob} > \text{Chi}^2 = 0.254$).

RE effect specification ($\text{Chi}^2 = 83.31$) suggesting a positive correlation between our dependent variables and the error term, as expected from our general empirical strategy.

⁴ Model 6 is specified without instrumenting each time period as in Model 5, so using one instrument for each variable and lag distance. In fact, the instrument is Model 5 are 23, while in model 6 are only 3. This is performed specifying the option “collapse” in the “xtabond2” STATA command (Roodman, 2009).

Add Table 2

Overall, the results suggest that our empirical strategy appropriately models both the endogeneity issue of the relationship between Mobility and Scientific Productivity, and the autocorrelation problem generated by estimating models with lagged dependent variables as predictors. Once modeling these significant sources of bias, our estimates show a positive causal relationship between the number individual mobility events in her carrier and the count of publications of each individual over time.

DISCUSSION AND CONCLUSION

In this paper we analyze the relationship between mobility and individual performance using an instrumental variable approach and dynamic panel data modelling. The key finding of this paper is that individuals who move across institutions increase their individual performance.

With this work we attempt to address important issues we believe have influenced the results obtained so far in studies on talented employees' mobility. First of all, we believe that specific environmental and organizational factors play a fundamental role in shaping not only the relationship between performance and mobility, but also the related portability of the competitive advantage generated by talented human capital. Therefore the choice of context of analysis becomes crucial in determining what kind of effect we will likely observe in the data, ultimately affecting our theoretical understanding of the phenomenon. We tried to relax some of the

assumptions deriving from specific contextual factors in knowledge-intensive industries (for example semiconductors or pharmaceuticals), which are usually subject of empirical research on employees' mobility. In particular, by examining the academic sector, we make predictions in a context in which knowledge assets represented by the individual human capital are less embedded in the organizational routines, thus, facilitating a stronger ownership and use by each individual of her own human capital. This implies that both the appropriability of the human capital and its portability across organizations is more likely to happen, necessary conditions to hypothesize a positive relationship between inter-organizational mobility and individual performance.

Second, we aim to address the issue of endogeneity caused by the bi-directional nature of the relationship between mobility and performance. Following recent efforts in the literature to deal with such endogeneity (Fernández-Zubieta et al., 2013; Groysberg et al., 2008; Hoisl, 2007; Singh & Agrawal, 2011), we model the effect of mobility on individual performance. While we recognize that these two variables are linked through a feedback loop, in this paper we aim at analyzing only one direction of the relationship. In order to identify our model correctly, we employ an instrumental variable, the number of students enrolled in the university of affiliation, which we argue affects mobility but not scientific productivity, because of the funding structure of the university sector in the UK. Taking advantage of the balanced panel structure of our data, we also model the dynamic nature of scientific productivity by using Arellano-Bond GMM estimators.

These two issues are also central to the contributions we aim to make with this paper. As discussed just above, by building on recent empirical work in this area, we believe our empirical strategy further improves the identification of the relationship between mobility and individual

performance. Moreover, we examine a context in which individual mobility is extremely relevant and frequent (Fernández-Zubieta et al., 2013). Finally, we also contribute to the literature in the economics of science tradition on the determinants of scientific productivity. While many individual (such as age, gender, position, discipline of affiliation) and organizational (quality of the institution, size of the institution, peers' productivity) characteristics have been put forward in the literature to explain what determines researchers' productivity (Azoulay, Graff Zivin, & Wang, 2010; Borjas & Doran, 2012; Carayol & Matt, 2006; Stephan, 1996; Waldinger, 2012), only few contributions have focused on the effect of mobility (Allison & Long, 1990; Dietz & Bozeman, 2005; Fernández-Zubieta et al., 2013). In our analysis we show that even after taking into account individual characteristics, academics who are more mobile tend to increase their productivity.

Notwithstanding the effort we put in modelling the relationship between mobility and individual performance, results need to be interpreted taking into account the limitations of our study, which in turn open up possibilities for future research. First of all, more effort is required in order to better characterize organizational features which are liable to change over time. While we have information on the number of students enrolled every year, our study does not include measures of quality or amount of resources at the organizational level. Furthermore, in our analysis we do not take into account the effect of departmental colleagues' on individual productivity, effect which has been shown to be relevant in determining researchers' scientific productivity (Azoulay et al., 2010; Borjas & Doran, 2012; Waldinger, 2012). Regarding the research design, our model only investigates one direction of the mobility-productivity relationship. As we recognize the inherent bi-directionality of this relationship, future research should further investigate both directions in order to assess not only the impact of mobility on performance, but also how performance influence the likelihood of individuals moving in the first place. Finally, our paper offers an attempt to model potential endogeneity biases of

the research stream on mobility. In this sense, and IV along with an Arellano-Bond identification strategy seems to be an appropriate way of dealing with the empirical challenges above-mentioned. While our results confirm our empirical strategy as valid, future research should continue to explore currently developed empirical strategies, as matching estimators and difference-in-difference estimators (Azoulay et al., 2010; Groyberg et al., 2008; Singh & Agrawal, 2011) in order to improve the precision in the estimation process and the related interpretation. And this is especially relevant when it comes to model the unobserved heterogeneity typical of the research on mobility in innovative contexts, where the scarcity of data presents important challenges to any empirical researcher interested in this field.

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FIGURES AND TABLES

Figure 1: Distribution of individual scientific productivity

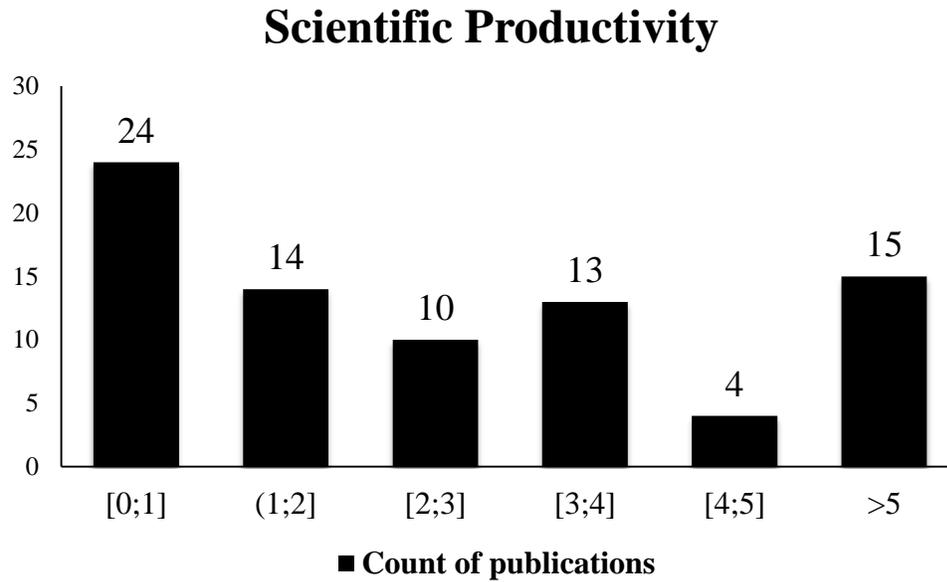


Figure 2: Frequency of number of moves (N=80)

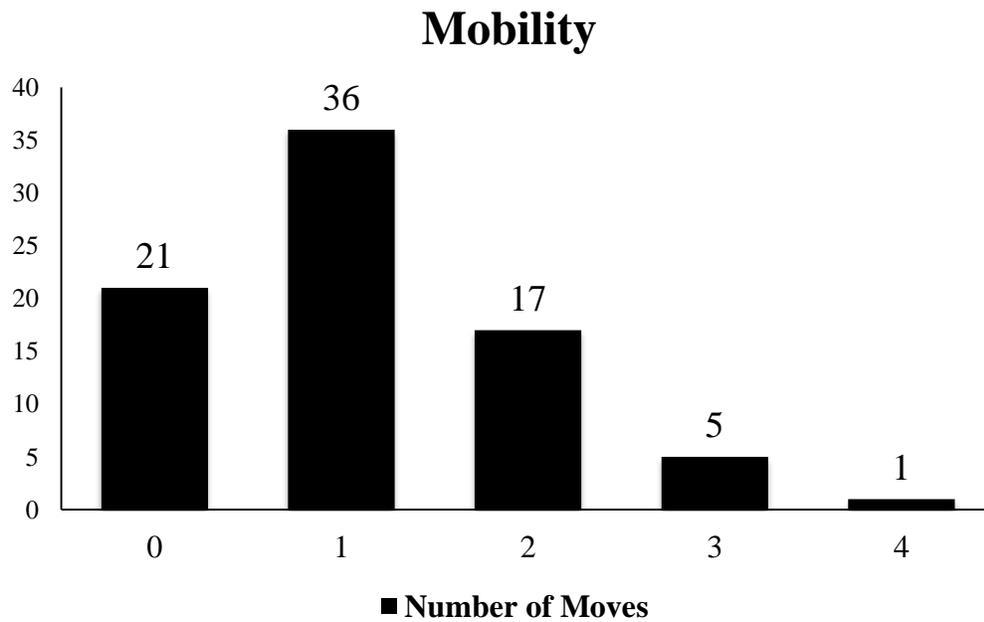


Table 1

Table 1: Different model specifications for <i>Scientific Productivity</i>												
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	OLS Fixed-Effects (No IV)		OLS Random-Effects (No IV)		OLS Fixed-Effects (IV second stage)		OLS Random-Effects (IV second stage)		Arellano-Bond 1 (IV second stage)		Arellano-Bond 2 (IV second stage)	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
MOBILITY	0.56*	0.25	0.33	0.22	2.36**	0.85	3.02**	0.99	2.79*	1.21	4.32**	1.42
SCIENTIFIC PRODUCTIVITY (LAGGED T-1)					0.27***	0.04	0.41***	0.04	0.12	0.08	0.81	0.10
Wald Chi2					1850.13***		135.60***		6.2*		9.22**	
F	5.02*		2.24									
Number of groups	80		80		80		80		80		80	
N	914		914		834		834		754		754	

Table 2

Table 2: Arellano-Bond model specifications for <i>Scientific Productivity</i>				
	Model 5		Model 6	
	Arellano-Bond 1 (IV)		Arellano-Bond 2 (IV)	
	Coef.	Std. Err.	Coef.	Std. Err.
MOBILITY	2.79*	1.21	4.32**	1.42
SCIENTIFIC PRODUCTIVITY (LAGGED T-1)	0.12	0.08	0.81	0.10
Wald Chi2	6.2*		9.22**	
AR(1) z-value	-8.18***		-5.54***	
AR(2) z-value	1.37		1.01	
Sargan test (Chi2) for IV	0.907		0.254	

APPENDIX

Appendix 1

Appendix 1: First Stage of Model 3 and 4 with <i>Students Enrolled</i> as IV for <i>Mobility</i>					
	Model 3			Model 4	
	OLS Fixed-Effects (IV first stage)			OLS Random-Effects (IV first stage)	
	Coef. (x1000)	Std. Err. (x1000)		Coef. (x1000)	Std. Err. (x1000)
STUDENTS ENROLLED	0.02***	0.00		0.02***	0.00
SCIENTIFIC PRODUCTIVITY (LAGGED T-1)	7.34	4.49		0.57	5.30
F	55.01***				
Wald Chi2				53***	
Number of groups	80			80	
N	834			834	