Scientometrics (2015) 104:629–650
DOI 10.1007/s11192-015-1625-3

Job mobility, peer effects, and research productivity in economics

Thomas Bolli[1] **· Jörg Schläpfer**[1]

Received: 18 August 2014 / Published online: 21 June 2015

Abstract We analyse a comprehensive panel dataset of economists working at Austrian, German, and Swiss universities and investigate how job mobility and characteristics of other researchers working at the same university affect research productivity. On aggregate, we find no influence of these local research characteristics on the productivity of researchers, if we control for their unobserved characteristics. This finding indicates that with today's information, communication and travelling technologies knowledge spillovers are globally available rather than dependent on physical co-presence. However, we find some evidence that high-productivity researchers could be more likely to benefit from local research characteristics.

Keywords University · Economics · Productivity · Mobility · Peer effects · Bibliometrics

Mathematics Subject Classification 91B68 · 91B38

JEL classification I23 · J62

Introduction

Kenneth Arrow thought that " there is plenty of reason to suppose that the individual talents count for a good deal more than the firm as an organization." (Arrow 1962, p. 624) His statement points at three sources of productivity, namely the personal characteristics of its members, the synergy effects that emerge if these members collaborate effectively and the design of the organizational environment. This study explores the relevance of the

✉ Jörg Schläpfer
schlaepfer@kof.ethz.ch

Thomas Bolli
bolli@kof.ethz.ch

1 KOF Swiss Economic Institute, ETH Zurich, Leonhardstrasse 21, 8092 Zurich, Switzerland

second determinant for scientists - the extent to which the local research environment affects the productivity of academic researchers.

In this context, job mobility plays a special role. It is generally believed that mobility increases the productivity of scientists, and hence the EU has initiated the European Research Area (EU Commission 2000). As a result, the EU has removed legal and administrative obstacles of job mobility in the science system in order to foster mobility (EU Commission 2007). Yet, empirical studies so far suggest mixed correlations between academic mobility and research output. Moreover, the causal impact of mobility and the local research environment characteristics on research productivity is unclear (Bauder 2012; Fernandez-Zubieta et al. 2013).

To shed some more light on this thorny issue of causality we analyse a comprehensive dataset providing extensive bibliometric and personal information about all research active economists at universities in the German-speaking area between the years 2004– 2008. The main interest lies in the influence of job mobility from one university to another, local peer effects measured by the research productivity of the colleagues and matching quality indicated by the share of peers in overlapping research areas and the presence of co-authors in the department. We follow the empirical setup in Carayol and Matt (2006) and Dubois et al. (2012) and identify the effects of the local research environment on research productivity by exploiting within-individual variation. Additionally, the data allows us to control for unobserved heterogeneity across universities.

We extend the existing evidence of the effect of the local environment on research productivity in various directions. First, our sample comprises the full sample of research active professors in economics in the German-speaking area and our quality weighted measure of research productivity is based on 1291 journals. In contrast the samples of similar studies either analyse a selected subgroup of researchers or the breadth of considered journals is limited (Dubois et al. 2012; Kim et al. 2009; Fernandez-Zubieta et al. 2013; Azoulay et al. 2010; Waldinger 2012). While Borjas et al. (2014) use a large sample as well, they assign no quality to the number of publications.

Our empirical results indicate no significant impact of the local research environment on productivity on average. Therefore, the empirical results support our baseline hypothesis suggesting that knowledge spillovers have lost their local nature due to the progress in information, communication and travelling technology (Kim et al. 2009). However, our results also support the relevance of absorptive capacity of researchers. Concretely, splitting the sample into low and high productivity researchers, we find some evidence that high productivity researchers are affected by the quality of the local research environment while low productivity researchers are not affected at all. This suggests that the external validity of research focusing on top researchers is limited and that the heterogeneity of the effect needs to be accounted for when designing policies.

Secondly, we improve upon empirical specifications used in the literature. For example we simultaneously test closely related hypotheses and our measurement of the productivity of all faculty members is more precise than using faculty rankings as a proxy. Furthermore, our data allows to control for unobserved heterogeneity of both individuals and universities, and our set of control variables is rich, including the control variables age, gender, sub-field, academic position, and size of institution.

Thirdly, we provide first results for European economists rather than mathematicians or natural scientists (Dubois et al. 2012; Waldinger 2010, 2012; Fernandez-Zubieta et al. 2013) and medical scientists (Azoulay et al. 2010) or economists in the US (Kim et al. 2009). Economists are particularly suited to such an analysis based on bibliometric measures for several reasons. For our sample of researchers quality-rated journals are the most important publication outlet in contrast to for example books, blogs or monographs. In addition, we can attribute the output to individual researchers, because the publications are generally written by a small number of authors and no weighting of the first authors is required. Furthermore, capital in the form of e.g. laboratories or computing power is less relevant than in natural sciences. This characteristic eases the task of disentangling peer effects from other forms of local characteristics, but also implies that our results may not hold for disciplines where capital is more important.

Fourthly, we extend the dimension of local environment characteristics by showing that matching quality measured by the share of peers working in the same sub-field has no effect on productivity. Similarly, we find no impact of the share of incoming researchers in a university after controlling for peer quality, suggesting that the novelty of their inputs has no significant effect on research productivity.

The next section describes the framework of research productivity resulting in our hypotheses. Section three describes the data and the methodology of the empirical part. The results are presented in section four and discussed subsequently.

Framework

Locality of knowledge spillovers

Knowledge spillovers are flows from one unit to another unit (Dietz and Bozeman 2005), and represent a central theme in the productivity (see, e.g. Stoyanov and Zubanov 2012) and innovation literature (Cohen and Levinthal 1989, 1990; Cassiman 2002). In academia, knowledge spillovers occur for example when researchers discuss with each other and are particularly important due to the non-rival nature of academic knowledge (Jaffe et al. 2000). In contrast, firm boundaries prevent knowledge from flowing freely and spilling over across firms in the private sector. Furthermore, academics can work on the same projects even at the new institution.

While spillovers can materialize whenever people collaborate, the question at hand is whether spillovers are globally available or rather are locally bound, for example at the university as the working place. This question about the locality of knowledge spillovers is widely debated for example in the regional innovation literature (see, e.g., Leamer and Storper 2001; Sonn and Storper 2008). Spillovers might be locally bound (Walckiers 2008) and might require physical co-presence (Boschma 2005) for several reasons: For example because the transfer of tacit knowledge, i.e. the uncodifiable and complex knowledge (Polany 1967), requires trust and understanding which develop easier through face-to-face contacts (Simmie 2005; Griffith et al. 2011) or because communication costs might be lower for researchers working at the same university (Elhorst and Zigova 2014).

However, lower cost and improved availability of travelling and communicating across distances as well as the development of English as the standard language in academia loosens the interdependence between a researcher and his colleagues at the same university (Kim et al. 2009; Rosenblat and Möbius 2004). Hence, we state the following baseline hypothesis:

Baseline hypothesis *In academic research, spillovers are not locally bound.*

Kim et al. (2009) supports the hypothesis by showing that being affiliated with a top university had a positive causal effect on productivity in the 1970s, but that this effect has vanished more recently. Similarly, Thompson and Fox-Kean (2005) find at best modest geographical boundaries and Griffith et al. (2011) conclude that geographic bounds have declined over time. Indirect evidence for the baseline hypothesis is given by the evidence suggesting that networks are becoming more global (Goyal et al. 2006; Laband and Tollison 2000; Jonkers and Tijssen 2008; Katz and Martin 1997; Wuchty et al. 2007).

We test the baseline hypothesis indirectly. Concretely, we approximate the local research environment by job mobility, the quality of peers and the match between researcher and university and test whether these variables affect the productivity of individual researchers. Assuming that knowledge spillovers exist, these variables for the local research environment test the baseline hypothesis that knowledge spillovers in academia are global and not locally bound. Hence, an insignificant effect of the local research environment provides suggestive evidence for the baseline hypothesis.

Peer effects

In order to test the baseline hypothesis, we first explore whether the quality of peers increases productivity, capturing the idea that higher quality peers provide more spillovers arising from ideas, feedback and formal or informal collaboration and researchers (Walckiers 2008):[1]

Hypothesis 1a *The productivity of peers at a university increases research productivity.*

The empirical evidence about peer effects in academia is mixed. Allison and Long (1990) or Carayol and Matt (2006) document a sizeable correlation between the quality of peers and productivity. More recent studies that attempt to identify the causal impact, however, present ambiguous findings of the peer effects at the university level. Studying a sample of economists, Kim et al. (2009) find that the causal effect of the location-specific component has vanished over the last decades. In another recent analysis of an exhaustive bibliometric database for mathematicians, Dubois et al. (2012) conclude that the local interaction effect is not important. Regarding mentoring of doctoral students, knowledge externalities are confirmed in a study by Waldinger (2010), who convincingly uses the expulsion of Jewish scholars by the Nazi regime as an exogenous variation to the productivity of the faculty. However, in a second study Waldinger (2012) uses the same exogenous variation and finds no peer effect among the senior faculty, reflecting the fact that senior researchers draw on an established network (Waldinger 2010). Cohen and Levinthal (1989, 1990) argue that knowledge spillovers increase in the absorptive capacity of the firm. In analogy, we expect that research productivity of an individual increases the capacity to absorb knowledge spillovers. Therefore, we hypothesize that:

Hypothesis 1b *Peer effects are higher for high productivity researchers than for low productivity researchers.*

Matching with the faculty

A better match between the researcher and the university increases knowledge spillovers if these have a local nature, ceteris paribus. Hence, a better job match enhances productivity

[1] Furthermore, peers might additionally influence research productivity by creating a competitive environment in which peers at the same university align their efforts (Frank 1985).

as suggested by the matching theory (Topel and Ward 1992; Hoisl 2009). In analogy we state that:

Hypothesis 2 *A better match with the faculty increases productivity.*

Empirical evidence for this hypothesis is rather scant. Borjas et al. (2014) distinguish three dimensions of matching with peers (similar ideas, same university and co-authorships) and do not find a statistically significant effect of a knowledge supply shock of the research productivity of the average researcher.[2] Azoulay et al. (2010) find that the effect of a superstar death on co-author productivity is most pronounced if the co-author is located closely in the intellectual space, i.e. if the co-author works in a similar area. Furthermore, while Waldinger (2012) finds no effect of departmental peer quality, he finds that the quality of co-authors does matter, suggesting that the match between the researcher and the department might affect knowledge spillovers.

Job mobility

Job mobility and research productivity are interlinked in several ways. Firstly, job mobility affects the quality of peers and often improves the match between the researcher and the university (Topel and Ward 1992; Jovanovic 1979). In the framework of Fernandez-Zubieta et al. (2013), acceptance of a job offer occurs if the improvement in the local research environment offsets moving costs, ceteris paribus.

Secondly, conditional on a given quality of the research environment, switching jobs exposes the researcher to ideas of new colleagues (Bäker 2013; Hoisl 2007; Hoch 1987; Jonkers and Tijssen 2008) that can be productively recombined with his existing skills to arrive at new insights (Katz and Martin 1997; Weitzman 1998). A job move, however, also incurs moving costs such as adapting to a new environment or teaching different courses. As a result of all these arguments and assuming that knowledge spillovers are local the pure mobility effect, i.e. the relationship between job mobility and research productivity after accounting for the local research environment, is ambiguous from a theoretical perspective. Related to the political perspective that job mobility is beneficial (EU Commission 2007), we test whether:

Hypothesis 3a *Job mobility increases research productivity.*

The available empirical evidence related to hypothesis 3a is mixed. While Jonkers and Tijssen (2008) find a positive correlation between mobility and productivity for China, Cañibano et al. (2008) find little evidence for Spain. However, limited evidence regarding the causal effect exists (Fernandez-Zubieta et al. 2013). Dubois et al. (2012) suggests that a move slightly increases future research output. The study by Fernandez-Zubieta et al. (2013) concludes that mobility increases output only if the job changes occur to an institution with better reputation. Results from the more developed patent literature suggest a positive impact of mobility (see, e.g., Carayol 2007; Dietz and Bozeman 2005; Hoisl 2007, 2009), but this might be due to the fact that firm boundaries make spillovers local. In analogy to hypothesis 1b, we hypothesize that absorptive capacity matters for the impact of job mobility on productivity as supported by the patent literature (Hoisl 2009):

[2] Early work by Lotka (1926); Beaver and Rosen 1979) document a positive correlation between the number of co-authorships and research productivity. A more recent study by Lee and Bozeman (2005) finds no impact of co-authorships when adjusting research productivity by the number of authors and when controlling for individual and institutional factors.

Hypothesis 3b *Mobility increases the productivity of high productivity researchers more than for low productivity researchers.*

Exposure to new ideas in the spirit of Weitzman (1998) arises not only in the case of job mobility, but also if peers change, suggesting that mobility generates an externality for the new team (Trajtenberg 2006) as the team might benefit e.g. from another background and from explicit and tacit knowledge spillovers (Barjak and Robinson 2008; Hoisl 2009; Schankerman et al. 2006). Hence, we test whether:

Hypothesis 3c *The share of incoming researchers at a university increases productivity.*

Mobility might occur for reasons that are not productivity related, e.g. involuntary moves (Bergman 2011) or moves due to personal motives, e.g. family or status (Frank 1985). Personal motives are modelled in Fernandez-Zubieta et al. (2013) by allowing the cost of moving to depend on personal characteristics. If the motive for mobility is unrelated to productivity, we expect that the research environment and match improves less than if the motive for mobility was to improve productivity. Assuming that upward mobility is correlated with productivity-related motives while downward mobility is related to other motives, we postulate the following hypothesis:

Hypothesis 4 *Upward mobility increases productivity more than downward mobility.*

Fernandez-Zubieta et al. (2013) documents a positive impact of the job mobility on research productivity if and only if the motive for job mobility was productivity oriented.

Methods

Sample

The data used in this study originates from the webportal *Forschungsmonitoring*, which collects output in peer-reviewed journals, basic demographic characteristics, academic title and sub-fields of specialization of economic researchers who work at Austrian, German and Swiss universities, or have an Austrian, German or Swiss citizenship. This platform has been initiated by the German Economic Association and is administrated at KOF Swiss Economic Institute at the ETH Zurich. The webportal is used to calculate the *Handelsblatt* rankings, the most visible evaluations of the research output of economists and their departments in Austria, Germany and Switzerland (Handelsblatt 2011a). There is an ongoing debate about the incentives created by rankings (see, e.g., Adler and Harzing 2009; Saisana et al. 2011). While this research article cannot not reshape any incentives, the publicity of the *Handelsblatt* ranking improves the quality of the *Forschungsmonitoring* database. As a result of all the manual work invested by individual researchers, their institutions and the administrators of the database in the forefront of a *Handelsblatt* ranking, the accuracy of the relational data in *Forschungsmonitoring* is relatively high for bibliometric data, where purely automatic data processing often results in mismatches.

We use information in *Forschungsmonitoring* gathered for the years 2006, 2007, 2008, 2010, 2011. A faculty roaster for the year 2004 published in Rauber and Ursprung (2008a) complements the list of affiliations. Yet our observations of economists eventually are restricted to the years 2006, 2007 and 2008 for two reasons: The measurement of productivity at time t refers to the average of $t+2$ and $t+3$ to account for publication lags, and on the other hand mobility refers to movement between $t-1$ and t.

In principle, our sample represents the full population of research-active economists at German-speaking universities in Austria, Germany and Switzerland. However, due to the time-lag in our measure of research output, some researchers drop out of the sample, because we do not have information concerning their publications in the years 2010 and 2011. While we know the publication record of German-speaking researchers who move to a non-German-speaking university, we lack information concerning non-German-speaking researchers who move to a non-German-speaking university and concerning researchers who leave academia. However, the second group is a minority (Dubois et al. 2012) and the last group typically ceases to publish in refereed journals. Affiliation data for the five French or Italian-speaking Universities in Switzerland are comprehensively collected only for later periods. We exclude emeriti from the sample and also drop 13 observations in which obtaining tenured occurs together with a switch of universities (Rauber and Ursprung 2008b). After all, obtaining the first chair could induce endogeneity, because it is associated with a particular impact on research output. We drop departments with less than five researchers in the previous period (Wolf et al. 2006) to ensure the consistency of our peer effect variables. Finally, we drop individuals for which we have only a single observation. This leaves us with 1194 observations of 498 economists at 48 universities.

Dependent variable—research productivity

Our measure of productivity, y_{it} is quantified with a bibliometric measure of individual i at time t, namely the quality weighted sum of articles divided by the average number of authors per article.[3] While research papers carry full points, comments and replies earn half of the points, and editorials and chapters in books obtain no points (Handelsblatt 2011b).[4] The relative weighting of the journal quality plays a crucial role in measuring research productivity. Based on Combes and Linnemer (2010) and Handelsblatt (2011a), the employed data uses weights that allocate one of seven weights between 0.05 and 1 to 1291 peer-reviewed journals - including all journals indexed in EconLit. The advantage of considering a broad set of journals is that also researchers from departments and cohorts that typically do not frequently publish in a more selective list of journals are represented.[5]

[3] Note that in economics the authors typically are named in alphabetical order.

[4] Even though bibliometric methods are imperfect measures of research productivity, they are widely used by university researchers, administrators and their stakeholders (see, e.g., Stephan 2012). Our data performs relatively well according to the quality criteria set out in Harzing (2008) and Adler and Harzing (2009). Concretely, we account for number of authors and the quality of a broad range of general as well as specialized journals that cover the relevant languages. Furthermore, in economics, no weighting of the first author is required and we control for the sub-field of specialization. Finally, we appropriately assign affiliations by using the current and primary affiliation.

[5] Publications in peer-reviewed journals are the most important publication outlets in our sample of economists at German-speaking universities. In the time span under consideration, books and monographs have lost some of their previous high importance and blogs have only started to become important. Assigning a quality weight to a journal is preferred to pure counting of publications or citations and reflects the screening in the review process. Nonetheless, journal rankings based among other criteria on impact factors have a limited explanatory power for the impact of the individual article (early work on this topic include Schubert and Glänzel (1983) and Seglen (1997)). However, for example using instead article citations to account for quality is not possible in the current setting, because in economics with its particular long publication time lag, using citations as a reliable quality measure requires several years of subsequent observations.

Our measurement of research productivity is the same for every year, despite the fact that the methodology of the *Handelsblatt* ranking has changed over the years.[6] Finally, the counts of a researcher are added up per year. For example one single-authored research article published in the Quarterly Journal of Economics yields 1 count and another research article written by three authors in the Journal of Labour Economics, a journal with a weight of 0.6, yields 0.2 counts for a total of 1.2 counts.

We assume a lag of two to three years between the research process and the publication date, based on Ellison (2002), who reports an average time lag between submission and acceptance of between nine and 29 months for thirty top journals in economics. In order to relax our assumption, we smooth output and flatten short-term effects by using the average (Beckmann and Schneider 2011) over two years of research output as rolling window (Levin and Stephan 1991).

Variables testing the hypotheses

One of the crucial explanatory variable is $Mobil_{i,t}$, a dummy variable indicating whether an economist i moves permanently to another university in the German-speaking area between $t-1$ and t.[7] In order to test hypothesis 1a, i.e. whether research productivity of peers increases individual research productivity, the variable $\bar{y}_{-i,j_t,t-1}$ captures the average research productivity of the peers, evaluated at time $t-1$. The subscript $-i$ refers to all economists except researcher i working at the same university as researcher i and the subscript j_t denotes the university the individual is working at in year t. We explicitly indicate j_t to illustrate the construction of the variables and because the timing is important and non-trivial as described below.

In order to test hypothesis 2, we operationalize the match between the researcher with the local research environment by overlapping sub-fields with peers and having a co-author at the university. Concretely, $\overline{Field}_{-i,j_t,t-1}$ measures the share of peers that have at least one sub-field in common with the researcher. Building on Rauber and Ursprung (2008b) we distinguish seven sub-fields, namely microeconomics, macroeconomics, public economics, econometrics, finance, other economics and business. $Coauthor_{i,j_{t-1},t-1}$ is a dummy variable that indicates whether the researcher works in year t-1 with a co-author from the same university.

The yearly fraction of the faculty at university j excluding researcher i that has moved in from another university is denoted by $IncomingShare_{-i,j_t,t-1}$. This variable tests whether mobility creates externalities for the new team in line with the theory of Weitzman (1998) about the fruitful recombination of new ideas (hypothesis 3c). Furthermore, this variable also controls for differences in turnover frequencies across universities.

These contemporary peer characteristics are university specific and they are linked to individual i, who influences his peer group. In order to address this so-called reflection problem (Manski 1993), we follow Hanushek et al. (2003) and Vigidor and Nechyba (2007) and lag backward all peer characteristics by one year and use these lagged values as instruments for of the current values. As a result of this instrumenting approach we can rule out feedback effects from an individual researcher to his peers. Formally, lagging the peer characteristics of individual

[6] For more information regarding the methodology of the *Handelsblatt* ranking 2011 used in this study refer to Handelsblatt (2011b).

[7] Since we control for the local research environment, $Mobil_{i,t}$ identifies the pure mobility effect (hypothesis 3a), i.e. the job mobility effect for a given local research environment. Including $Mobil_{i,t}$ and $\bar{y}_{-i}$ individually yields qualitatively the same results, suggesting that multicollinearity is not a major concern. These estimates can be obtained from the authors upon request.

i currently working at university j_t by one year implies that the last subscript indicating the time dimension is $t-1$. As a result the subscripts of the peer characteristics are as follows: $\overline{y}_{-i,j_t,t-1}$, $\overline{Field}_{-i,j_t,t-1}$, and $IncomingShare_{-i,j_t,t-1}$. The same subscripts apply whether the researcher switches job or stays at the same university. Thus, in case of a move we instrument average peer characteristics at the new university j_t with their lagged value rather than with their average peer characteristics of the former university.

While in principle all variables are always related to the current university, there is one exception: The variable $Coauthor_{i,j_{t-1},t-1}$, is taken with reference to the university the researcher worked at in the previous year, indicated by the subscript j_{t-1}. Using a dummy variable that indicates whether the individual has a co-author at the new institution would be problematic for two reasons. First, finding a co-author in the first year might reflect social capital of the individual rather than matching quality. Secondly, lagging the variable suggests potential endogeneity of the co-author dummy with the mobility dummy, as the presence of a co-author at a future university might induce mobility. Thus, for mobile and immobile researcher, the dummy variable $Coauthor_{i,j_{t-1},t-1}$, takes the value 1 if one of the co-authors works at the same university j_{t-1}, thus referring to the university the researcher was employed at time $t-1$.

Control variables

Matrix $Z_{i,j_t,t-1}$ captures the institutional control variables. The number of economists per university ($Size_{i,j_t,t-1}$) enters in a quadratic form to account for non-linear relationships (see, e.g., Fabel et al. 2008). Research output can be related to the size of the institution and according to the concept of a critical mass there is a minimal size of a research group in order to sustain (Ralph and Bertrand 2011). As discussed above the values of the institutional control variables are lagged by one year to circumvent the reflection problem (Manski 1993). Matrix $X_{i,t}$ captures the individual control variables. Concretely, building on the theoretical model of Levin and Stephan (1991), the literature about life-time patterns of academics suggests that research productivity of economists follows a hump-shaped pattern. We control in a quadratic form for career age—defined as years since the Ph.D. thesis—and label it $Experience_{i,t}$. This literature strand further suggests that obtaining the first tenured position is a crucial event. While promotion reflects a selection effect and generally increases the resources (Carayol and Matt 2006), research productivity usually declines after obtaining a permanent job at least to a small extent (Beckmann and Schneider 2011), suggesting that extrinsic motivation plays an important role in the publication process (see, e.g., Rauber and Ursprung 2008b; Backes-Gellner and Schlinghoff 2010). Hence, we include a dummy variable, $Tenured_i$, to indicate whether a researcher has already received his first call, i.e. whether a person is a professor.[8] We further control for the $Gender_i$ and the $Subfield_i$ of specialisation. Table 1 lists the definition of all variables.

Regression equation

In a linear reduced form equation we estimate individual and institutional determinants of individual research productivity in analogy to Carayol and Matt (2006). Formally, our pooled OLS (POLS) estimation equation has the following appearance:

[8] By dropping observations for which receiving the first call and mobility coincide, the variable $Tenured_i$ becomes time-invariant.

Table 1 Definitions of the dependent and independent variables

y	Yearly publication output in *t*+2 and *t*+3, weighted by the 2011 *Handelsblatt* journal weights divided by the average number of authors
Mobil	Dummy variable that takes the value 1 if a researcher moved to a new university between $t-1$ and *t* and 0 otherwise
$\bar{y}_{-i}$	One year lagged average output of peers at the university affiliation in *t* (new university in case of a move)
$\overline{Field}$	One year lagged share of peers at the same university in *t* that share at least one sub-field as the researcher *i*
Coauthor	One year lagged dummy variable that takes the value 1 if a co-author of researcher *i* shares his affiliation in $t-1$ and 0 otherwise
Incoming share	One year lagged share of peers moving to the university
Size	One year lagged number of research active employees at the university affiliation at *t*–1
Tenured	Dummy variable that takes the value 1 if a researcher *i* has already received his first call and 0 otherwise
Experience	Years since receiving Ph.D. if known, otherwise years since first publication
Gender	The gender of researcher *i* is coded as 0 for men and 1 for women
Subfield	An economist *i* works in one or several of the following sub-fields: microeconomics, macroeconomics, public economics, econometrics, finance, business and other
Downward Mobil	A dummy variable that is 1 if a researcher moves and his new peers are on average equally or less productive than his former peers
Upward Mobil	A dummy variable that is 1 if a researcher moves and his new peers are on average more productive than his former peers

$$\begin{aligned}\ln y_{i,j_t,t} = {} & \alpha_0 + \alpha_t + \beta Mobil_{i,t} + \gamma \ln \bar{y}_{-i,j_t,t-1} + \delta_1 \ln \overline{Field}_{-i,j_t,t-1} \\ & + \delta_2 Coauthor_{i,j_{t-1},t-1} + \eta IncomingShare_{-i,j_t,t-1} + \theta X_{i,t} + \zeta Z_{i,j_t,t-1} + \epsilon_{i,t}\end{aligned} \tag{1}$$

The panel data consists of the two dimensions individual *i* in year *t*. The affiliation *j* is further reported to clarify how the data is constructed. As explained in detail above, the variable $y_{i,j_t,t}$ refers to the research productivity measured by quality and co-author weighted articles published in the years $t+2$ and $t+3$. The constant is denoted by α_0 and yearly time dummies α_t account for trends in publication behaviour. The error term $\epsilon_{i,t}$ is clustered by individuals (Dubois et al. 2012).

In order to induce an elasticity setting, all continuous variables enter in logarithmic form. In the basic regression we transform the variables into logarithms by adding 0.01 for technical reasons.[9] A necessary condition for a causal interpretation of the estimates requires that the residuals are mean independent from the main explanatory variables conditional on all the covariates (Dubois et al. 2012). However, the POLS might suffer from a bias due to unobserved heterogeneity. In a first attempt to capture unobserved heterogeneity we add, $y_{i,j_t,t-1}$, the lagged dependent variable (LDV) to the right-hand side of Eq. (1) to arrive at the LDV equation. Thereby, LDV serves as a proxy for time-constant

[9] Due to the large number of journals considered in this study in addition to using the rolling average of publications over two years, only about 10 % of our sample has no research output in a particular year. Hence, it is not surprising that dropping the 154 observations with $y_{i,j_t,t}$=0 or using replacement values of 1, 0.1 or 0.001 yield qualitatively the same results. These results can be obtained from the authors upon request.

research ability (Beckmann and Schneider 2011; Walckiers 2008) but does not account for differences in the levels of the explanatory variables. As a result, LDV removes differences in research ability but not in the propensity to move across economists.

Hence, the possibility of unobserved heterogeneity in explanatory variables remains a concern, for example because highly productive researchers are more likely to be offered a new job (Fernandez-Zubieta et al. 2013). We approach this concern and introduce individual dummy variables α_i to the right-hand side of Eq. (1) (Kim et al. 2009; Dubois et al. 2012) and label the columns of these estimates FE, which exploits within-individual variation only (Dubois et al. 2012).

Finally, we estimate a model that entails dummy variables for individuals α_i in addition to dummy variables for each university α_j. With this approach we control not only for individual specific characteristics but additionally also control for time-invariant unobserved heterogeneity in the university dimension, e.g. administrative efficiency, teaching intensity. These estimates are labelled FE-2.

In order to test the remaining hypotheses about job mobility, we report evidence in two extensions: (1) We test whether absorptive capacity matters for the presence of local spillovers as claimed in hypotheses 1b and 3b by splitting the sample into researchers with output above and below the median productivity. This sample split between low and high productivity productive researchers complements the existing literature, whose focus is rather on research published in a more restricted list of top journals or a restricted set of journals. (2) Furthermore, we test whether the impact of job mobility differs according to the motive of the move. Concretely, we split the variable $Mobil_{i,t}$ into two variables $Downward\ Mobil_{i,t}$ and $Upward\ Mobil_{i,t}$ to capture job mobility to a university with a higher average quality of peers and job mobility to a university that has equal or lower quality of peers as suggested in hypothesis 4.

Descriptive statistics

The usual descriptive statistics and the means of the variables by country and gender are presented in Table 2. The average research productivity is 0.19, the highest observed average research productivity for a university is 0.40. The standard deviation of $\overline{y}_{-i,j_t,t-1}$ is 41 % of its mean, which points to a relative high variation in our measurement of peer effects, in particular relative to using a university ranking in order to proxy the productivity of peers. 12 % of the researchers in our sample are women and on average, the researchers have been active in academia for eleven years. We observe 59 job moves, most of them in Germany, the country with the majority of observations. We assume them to be voluntary moves, because German professors cannot be fired. And in our sample 92 % of the observations are tenured researchers. The main reason for this high share is that our estimation strategy requires individuals to be observed between the years 2006 and 2011.

Results

The results of estimating Eq. (1) for the full sample are presented in the first four columns of Table 3. As explained next, the signs of the coefficients estimated by POLS generally are as expected. This finding reassures that our data is suited for this analysis. *Experience* has a negative sign, reflecting the fact that publication productivity decreases with age in a sample of mostly tenured researchers, as suggested by the life-cycle hypothesis (see, e.g.,

Table 2 Summary statistics of all variables before any logarithmic transformation, means overall as well as by country and by gender

Variable	Mean	SD	Min	Max	Mean			Mean	
					AU	CH	DE	M	F
y	0.19	0.23	0	1.85	0.12	0.29	0.19	0.20	0.12
Mobil	0.05		0	1	0.01	0.08	0.05	0.05	0.06
$\bar{y}_{-i}$	0.17	0.07	0.02	0.40	0.11	0.26	0.17	0.17	0.17
$\overline{Field}$	0.38	0.21	0	1	0.45	0.36	0.38	0.38	0.42
Coauthor	0.35		0	1	0.32	0.35	0.36	0.36	0.29
IncomingShare	0.11	0.15	0	1	0.03	0.20	0.11	0.11	0.11
Size	15.76	9.68	5	41	18.09	20.25	14.77	15.52	17.55
Experience	11.08	9.43	0	37	11.32	10.65	11.11	11.78	5.98
Tenured	0.92		0	1	0.96	0.94	0.91	0.92	0.93
Gender	0.12		0	1	0.20	0.08	0.11	0	1
Micro	0.35		0	1	0.43	0.35	0.33	0.33	0.49
Macro	0.33		0	1	0.39	0.405	0.31	0.34	0.22
Public	0.42		0	1	0.42	0.38	0.43	0.42	0.44
Econometrics	0.17		0	1	0.20	0.20	0.17	0.19	0.08
Finance	0.03		0	1	0.01	0.016	0.04	0.04	0
Business	0.01		0	1	0	0.02	0.013	0.01	0
Other subfield	0.06		0	1	0.12	0.08	0.05	0.06	0.09
Downward Mobil	0.02		0	1	0.01	0.03	0.03	0.02	0.03
Upward Mobil	0.02		0	1	0.00	0.05	0.03	0.02	0.02
N	1194				148	126	920	1051	143

Rauber and Ursprung 2008b). Similarly, *Tenured* has a negative sign, revealing the relevance of obtaining tenure as a motivation to publish. POLS estimates suggest no influence of *Size* on productivity, thus suggesting that the critical mass does not play an important role. *Gender* also has a negative sign, implying that the women researchers in our sample publish less than their male counterparts.

In line with hypothesis 1a, the first column of Table 3 confirms the expected positive and significant correlation between $\bar{y}_{-i}$ and y. However, accounting for individual research ability by including the LDV, the local research environment loses most of its impact. Furthermore, if controlling for unobserved heterogeneity of individuals and universities in the FE and the FE-2 settings, not all estimated coefficients for mobility and peer effects are positive anymore, and the coefficients are no more statistically significant. While this finding that local peer quality doesn't affect research productivity contradicts studies for private patents, it is in line with recent findings for academia by Waldinger (2012), Dubois et al. (2012) and Kim et al. (2009).

The estimates display a similar picture for the measures of the quality of the match between the researcher and the university. Concretely, neither having a co-author at the same university (*Coauthor*) nor the share of researchers within the same field ($\overline{Field}$) have a significant effect on research productivity after controlling for unobserved heterogeneity. Hence, we find no support for hypothesis 2. Using POLS yields positive and significant coefficient estimates for *Mobil*, which tests hypothesis 3a. However, accounting for

Table 3 Estimation results of research output

	Full sample				Low productivity				High productivity			
	POLS	LDV	FE	FE-2	POLS	LDV	FE	FE-2	POLS	LDV	FE	FE-2
Mobil	0.329**	0.162	−0.036	0.008	0.224	0.185	−0.236	−0.315	0.150	0.081	0.088	0.362**
	(0.157)	(0.109)	(0.128)	(0.146)	(0.191)	(0.198)	(0.272)	(0.281)	(0.116)	(0.089)	(0.148)	(0.175)
$\ln \overline{y}_{-i}$	0.441***	0.129*	0.034	−0.005	0.227**	0.041	−0.140	−0.222	0.112	0.094	0.243	0.330
	(0.107)	(0.068)	(0.155)	(0.185)	(0.111)	(0.098)	(0.275)	(0.291)	(0.083)	(0.068)	(0.177)	(0.221)
$ln\overline{Field}$	−0.115**	−0.043	0.026	0.041	−0.089	−0.071	0.043	0.031	0.034	0.036	−0.032	0.021
	(0.047)	(0.029)	(0.065)	(0.073)	(0.058)	(0.050)	(0.096)	(0.103)	(0.036)	(0.028)	(0.087)	(0.113)
Coauthor	0.607***	0.074	0.057	0.040	0.455***	0.212**	0.133	0.095	0.189**	0.013	−0.039	−0.084
	(0.086)	(0.060)	(0.111)	(0.112)	(0.099)	(0.091)	(0.170)	(0.182)	(0.075)	(0.059)	(0.151)	(0.149)
IncomingShare	0.046*	0.023	−0.005	−0.009	−0.009	0.003	−0.013	−0.024	0.041*	0.020	0.017	0.019
	(0.025)	(0.018)	(0.031)	(0.033)	(0.032)	(0.029)	(0.054)	(0.057)	(0.023)	(0.019)	(0.036)	(0.040)
Size	−0.440	−0.393	−0.475	−0.607	0.233	0.139	0.042	−0.010	−0.334	−0.392	−0.521	−0.586
	(0.559)	(0.413)	(0.716)	(0.748)	(0.677)	(0.622)	(1.224)	(1.267)	(0.503)	(0.439)	(0.802)	(0.859)
$Size^2$	0.114	0.101	0.101	0.109	−0.059	−0.032	−0.025	−0.054	0.065	0.081	0.107	0.142
	(0.108)	(0.079)	(0.138)	(0.147)	(0.130)	(0.121)	(0.244)	(0.257)	(0.095)	(0.084)	(0.157)	(0.174)
Experience	−0.000	−0.026*	0.177	0.172	0.004	−0.004	0.141	0.082	−0.000	−0.030*	0.172	0.215
	(0.025)	(0.015)	(0.306)	(0.311)	(0.024)	(0.019)	(0.515)	(0.544)	(0.022)	(0.016)	(0.354)	(0.341)
$Experience^2$	−0.022**	−0.008	0.026	0.024	−0.009	−0.005	0.028	0.016	−0.006	−0.003	0.017	0.023
	(0.010)	(0.006)	(0.062)	(0.063)	(0.009)	(0.008)	(0.106)	(0.112)	(0.008)	(0.006)	(0.070)	(0.070)
Tenured	−0.268*	−0.143			−0.096	−0.025			0.104	0.068		
	(0.148)	(0.097)			(0.228)	(0.194)			(0.111)	(0.084)		
Gender	−0.320**	−0.077			−0.066	−0.005			−0.292***	−0.130		
	(0.137)	(0.092)			(0.139)	(0.119)			(0.095)	(0.085)		

Table 3 continued

	Full sample				Low productivity				High productivity			
	POLS	LDV	FE	FE-2	POLS	LDV	FE	FE-2	POLS	LDV	FE	FE-2
Micro	0.173	0.120*			0.024	0.054			−0.037	−0.030		
	(0.110)	(0.070)			(0.119)	(0.097)			(0.088)	(0.070)		
Macro	0.087	0.083			0.166	0.171*			−0.026	−0.026		
	(0.114)	(0.070)			(0.121)	(0.097)			(0.098)	(0.077)		
Public	0.178	0.101			0.227*	0.177*			−0.003	−0.005		
	(0.108)	(0.068)			(0.118)	(0.099)			(0.086)	(0.065)		
Econometrics	−0.089	0.089			0.137	0.185			−0.209**	−0.093		
	(0.127)	(0.077)			(0.139)	(0.113)			(0.087)	(0.070)		
Finance	0.500*	0.383***			0.042	0.182			0.111	0.164		
	(0.293)	(0.136)			(0.310)	(0.196)			(0.230)	(0.138)		
Other sub − field	−0.097	0.013			0.104	0.161			−0.002	0.037		
	(0.187)	(0.103)			(0.188)	(0.135)			(0.141)	(0.125)		
Business	0.251	0.136			−0.671**	−0.593***			0.299	0.216		
	(0.523)	(0.290)			(0.321)	(0.206)			(0.230)	(0.159)		
LDV		0.657***				0.364***				0.386***		
		(0.028)				(0.042)				(0.039)		
α_t, X_i, Z_i	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
α_i	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
α_{j_t}	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES
N	1194	1194	1194	1194	591	591	591	591	603	603	603	603
R^2	0.149	0.479	0.795	0.802	0.084	0.200	0.609	0.623	0.072	0.255	0.585	0.615

Table 3 continued

	Full sample				Low productivity				High productivity			
	POLS	LDV	FE	FE-2	POLS	LDV	FE	FE-2	POLS	LDV	FE	FE-2
Adjusted R^2	0.134	0.470	0.643	0.640	0.052	0.171	0.292	0.294	0.040	0.228	0.278	0.283

Table 3 shows OLS coefficients and robust standard errors clustered at individual level in parentheses

*, ** and *** denote significance at the 10, 5 and 1 % level, respectively

The dependent variable is the logarithms of the number of publications, weighted by the quality of the journals and the average number of authors

The sample consists of economists working at a German-speaking university during the years 2004 to 2008 and considers their research published in the years 2008 to 2011

Estimates are shown for full sample and a split into researchers with above and below median productivity

Analysing the equality of coefficients across the low and high productivity sample using a simultaneous estimation for OLS, LDV and FE respectively yield p values of 0.74, 0.63, 0.16 and 0.01 for *Mobil*, 0.40, 0.65, 0.12 and 0.04 for $\bar{y}_{-i}$, 0.07, 0.06, 0.44 and 0.93 for $ln\overline{Field}$, 0.03, 0.06, 0.31 and 0.30 for *Coauthor* and 0.19, 0.62, 0.54 and 0.41 for *IncomingShare*

The share of the variance due to across-individual variance for the full sample, low and high productivity researchers respectively, are 0.72, 0.50, 0.52 in the FE equations and 0.79, 0.66, 0.77 in the FE-2 equations unobserved heterogeneity in the dependent variable (LDV) yields insignificant coefficient estimates. Similarly, the share of new researchers (*IncomingShare*) displays a significantly positive relationship with research productivity that vanishes after accounting for unobserved heterogeneity. Hence, we cannot confirm hypothesis 3c.

Summing up the evidence presented in the first four columns of Table 3, we do not find empirical evidence that the local research environment affects individual productivity. Hence, we cannot reject the baseline hypothesis, suggesting that knowledge spillovers are global rather than locally bound. The arguably explanation is that with the rise of internet and data, lower costs and better availability of travelling, of long-distance calls and of access to publications have enabled to communicate productively with colleagues from other universities (see, e.g., Kim et al. 2009; Griffith et al. 2011). This might be particularly true for economics where expensive laboratories and computing power are less relevant than in the natural sciences (Teodorescu 2000).

However, we further split the sample into low and high productivity researchers to test for absorptive capacity (hypotheses 1b and 3b). The corresponding results in columns 5-13 of Table 3 suggest that the average effect might disguise heterogeneity of the effect. Concretely, while low and high productivity researchers are relatively similar in terms of simple correlations, the FE-2 estimates for mobility are significantly positive for high productivity researchers and insignificantly negative for low productivity researchers. Testing equality of the coefficients based on a seemingly-unrelated regression, the null hypotheses of equality is rejected at a 5 %-significance level. Similarly, the coefficients for $\overline{y}_{-i}$ are significantly higher for high productivity researchers, though the point estimate for high productivity researchers is marginally insignificant. The corresponding tests for the matching variables $\overline{lnField}$ and *Coauthor* and the share of incoming researchers *IncomingShare* do not differ significantly between low and high productivity researchers, suggesting that the match between individual and university in these dimensions do not affect productivity.

Confirming hypotheses 1b and 3b suggests that the impact of the local research environment depends on the absorptive capacity of the researchers (Cohen and Levinthal, 1989, 1990). Hence, these findings suggesting a positive influence (Dubois et al. 2012) of the local research environment might not be valid for low productivity researchers. This heterogeneity of the effect needs to be taken into account when designing policies aimed to promote mobility.

Table 4 summarises the evaluation of the hypotheses based to the empirical results.

We address potential reverse causality between research productivity and measures of the local research environment in three dimension. First, our empirical framework accounts for unobserved heterogeneity at the level of individuals and universities. Second, we circumvent the so-called reflection problem by lagging the explanatory variables that could be prone to it. A third concern in the estimation strategy refers to the potential reverse causality between productivity and mobility, e.g. because more productive researchers receive more job offers or because sometimes the main motive to switch jobs is unrelated to productivity gains. In the main estimation, this problem is alleviated to some extent by the fact that our sample entails 92 % professors, suggesting that observed moves are voluntary.

Table 5 further provides a test for potential endogeneity of mobility by exploiting the fact that we can compare whether the average research productivity is lower at the old university before the move than at the new university after the move. In this situation we label a switching of a job upward mobility and we construct two mobility variables for

Table 4 Summary of the evaluations of the hypotheses

H	Description of hypotheses	Accepted
Base	Knowledge spillovers are global and not locally bound	Not rejected
H1a	Peer quality increases average research productivity	No
H1b	High productivity researchers benefit more from peer effects	Yes
H2	A good match of the faculty improves research productivity	No
H3a	Job mobility increases average research productivity	No
H3b	High productivity researchers benefit more from job mobility	Yes
H3c	The share of incoming researchers increases productivity	No
H4	Upward mobility increases productivity more than downward mobility	No

downward and upward mobility, respectively. In the case that our results are merely a product of endogeneity, we expect that upward mobility drives the positive effect of mobility while downward mobility is insignificant or even negative. The results shown in Table 5 actually display the opposite, i.e. a negative coefficient of upward mobility and a positive coefficient of downward mobility for low productivity researchers and a positive coefficient of similar magnitude of high productivity researchers. Even though both estimates are insignificant, this finding provides suggestive evidence that our findings are not due to reverse causality.

Discussion

Our results indicate that, on aggregate, the local research environment has an insignificant effect on research productivity. This finding supports our baseline hypothesis that suggest that knowledge spillovers are not bound at the local university. However, we do not interpret our results in a way that spillovers do not exist or that co-operations have no effects in research. Rather our results suggest that nowadays colleagues anywhere across the world can provide comments, feedback and new ideas (see, e.g., Laband and Tollison 2000; Stigler 1988). Incidentally, the internet was constructed originally at CERN with the intention to facilitate the exchange among scientists and it definitively is doing so (Rosenblat and Möbius 2004). The trend towards an open-access community and making presentation in seminars available online goes hand in hand with a diminished importance of affiliation. Our findings are at odds to the literature analysing patenting behaviour in private companies, highlighting the peculiarities of the academic knowledge production process and of the academic job market (Bauder 2012), which is particularly mobile, highly skilled and international (Ackers 2005).

The results about job mobility are based on 57 observations of job mobility. Another limit of this study is the fact that this paper focuses on the short run effects from mobility and is silent about potential long-term effects.[10] Long-term effects of mobility (Cañibano et al. 2008; Scellato et al. 2012), as for example expanding the network of co-authors, represent an important avenue for future research. Furthermore, mobility might increase

[10] In principle, it would be possible to analyse the impact delayed by one year by ignoring the data for the year 2008. However, this approach would leave us with a sample size of 442 observations, a time dimension of 2, and only 22 incidences of job mobility. In particular there is not enough data for a further sample split. Due to this data restriction we do not evaluate this additional impact lagged by one year.

Table 5 Estimations splitting mobility it into up- and downward mobility

	Full sample				Low productivity				High productivity			
	POLS	LDV	FE	FE-2	POLS	LDV	FE	FE-2	POLS	LDV	FE	FE-2
Upward Mobil	0.364*	0.204	−0.185	−0.212	0.167	0.226	−0.588*	−0.489	0.232	0.122	0.024	0.364
	(0.219)	(0.140)	(0.154)	(0.205)	(0.251)	(0.264)	(0.300)	(0.362)	(0.152)	(0.111)	(0.213)	(0.260)
Downward Mobil	0.292	0.118	0.129	0.267	0.281	0.145	0.097	0.008	0.061	0.037	0.164	0.361
	(0.208)	(0.164)	(0.168)	(0.180)	(0.283)	(0.302)	(0.379)	(0.193)	(0.167)	(0.138)	(0.160)	(0.219)
$\ln \bar{y}_{-i}$	0.442***	0.129*	0.020	−0.036	0.228**	0.040	−0.158	−0.237	0.116	0.095	0.234	0.330
	(0.108)	(0.068)	(0.156)	(0.190)	(0.111)	(0.098)	(0.276)	(0.294)	(0.084)	(0.069)	(0.181)	(0.235)
$ln\overline{Field}$	−0.115**	−0.043	0.030	0.044	−0.089	−0.071	0.047	0.030	0.033	0.035	−0.029	0.021
	(0.047)	(0.029)	(0.065)	(0.073)	(0.058)	(0.050)	(0.096)	(0.103)	(0.037)	(0.029)	(0.088)	(0.113)
Coauthor	0.606***	0.074	0.060	0.036	0.455***	0.212**	0.144	0.090	0.188**	0.013	−0.039	−0.084
	(0.086)	(0.060)	(0.111)	(0.113)	(0.099)	(0.091)	(0.169)	(0.183)	(0.075)	(0.059)	(0.152)	(0.149)
IncomingShare	0.047*	0.023	−0.007	−0.012	−0.009	0.004	−0.013	−0.024	0.043*	0.021	0.016	0.019
	(0.025)	(0.018)	(0.031)	(0.034)	(0.032)	(0.030)	(0.054)	(0.057)	(0.022)	(0.018)	(0.037)	(0.040)
LDV		0.657***				0.364***				0.386***		
		(0.028)				(0.042)				(0.039)		
α_t, X_i, Z_i	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
α_i	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
α_{j_t}	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES
N	1194	1194	1194	1194	591	591	591	591	603	603	603	603
R^2	0.149	0.479	0.796	0.803	0.084	0.201	0.611	0.624	0.073	0.255	0.585	0.615
Adjusted R^2	0.133	0.469	0.643	0.641	0.051	0.170	0.294	0.293	0.039	0.227	0.276	0.280

Table 5 shows OLS coefficients and robust standard errors clustered at individual level in parentheses

*, ** and *** denote significance at the 10, 5 and 1 % level, respectively

The dependent variable and the sample is the same as in table 3 the reputation and the visibility of a researcher and therefore also the career prospects (Bauder 2012). This suggestion is in line with the literature suggesting that network-related or salary bargaining motives are more important than productivity-related motives for job mobility (Ackers 2005; More 2010).

However, to the extent that mobility fosters the career but not productivity, our findings cast some doubt on the effectiveness of the intention of the European Research Area to improve research productivity by fostering permanent mobility. A promising policy route might be to focus resources and energy towards fostering network creation. The need for physical co-presence can also be attained by periodical travelling rather than the need for permanent geographical proximity (Boschma 2005). An important example is the support of international conferences, where researchers can meet, discuss and present their ideas (Weinberg 2006). Furthermore, fostering project co-operations also helps to establish contacts that might lead to important synergies in the future. Project-co-operations might be fostered by favouring co-operation projects in proposal evaluations or by creating co-operations among funding agencies, allowing for cross-border financing of projects as done for example in Swiss National Science Foundation (2014). Another promising policy route is to foster short-term mobility (Bauder 2012; Breuninger 2013). Such activities might substitute the need for switching jobs in order to connect to and match with appropriate peers.

This study further finds indications that high productivity researchers benefit more from the local research environment than low productivity researchers. This suggests that policies promoting permanent mobility should be geared towards high productivity researchers, while alternative means of fostering network creation are more appropriate for all researchers.

Our empirical analysis further reveals an important avenue for future research. We use a relatively crude measure of the quality of the job matches. Improving this measure would be an important step towards understanding the relationship between the local research environment and productivity. This is particularly true as we do not distinguish formal collaboration e.g. by publishing together from more informal sharing of thoughts, for example over coffee. Like any bibliometric measure our measurement of research productivity can be further improved, as we allocate a weight to an article based on the importance of its journal. Considering peer-reviewed journal articles only might be a reasonable way to approximate research output for economists in our sample. However, transferring the research findings to other disciplines might be limited due to idiosyncrasies of economics, in particular for research in the natural sciences where capital is more relevant.

Acknowledgments We thank Stephan Fretz and Heinrich Ursprung for ongoing support. For helpful comments and suggestions we are grateful to two anonymous referees, Toke Aidt, Matthias Bannert, Tobias Brändle, Martin Gassebner, Anne-Wil Harzing, Bertrand Koebel, Matthias Krapf, Michael Lamla, Martin Paldam, Marc Sangnier and Jan-Egbert Sturm. Furthermore, we are thankful to the participants of the KOF research seminar, of the Lancaster University Economics Department Research Seminar, of the Personnel economics colloquium in Tübingen, of the SMYE in Aarhus, of the EJPE workshop in Castasegna and of the EPCS conference in Cambridge.Thomas Bolli gratefully acknowledges the financial support of the Swiss National Science Foundation.

References

Ackers, L. (2005). Moving people and knowledge: Scientific mobility in the European Union. *International Migration*, *43*(5), 99–131.

Adler, N. J., & Harzing, A. W. (2009). When knowledge wins: Transcending the sense and nonsense of academic rankings. *Academy of Management Learning and Education*, *8*(1), 72–95.

Allison, P. D., & Long, J. S. (1990). Departmental effects on scientific productivity. *American Sociological Review*, *8*, 469–478.
Andrews, M., Schank, T., & Upward, R. (2006). Practical fixed-effects estimation methods for the three-way error-components model. *Stata Journal*, *6*(4), 461–481.
Arrow, K. (1962). Economic welfare and the allocation of resources for invention. *The rate and direction of inventive activity: Economic and social factors* (pp. 609–626). NBER Chapters: National Bureau of Economic Research Inc.
Azoulay, P., Graff Zivin, J., & Wang, J. (2010). Superstar extinction. *Quarterly Journal of Economics*, *25*, 549–589.
Backes-Gellner, U., & Schlinghoff, A. (2010). Career incentives and publish or perish in German and US universities. *European Education*, *42*(3), 26–52.
Bäker, A. (2013). The impact of changes of affiliation on publications: An analysis of the role of research discipline and institutional size. Working Paper Series.
Barjak, F., & Robinson, S. (2008). International collaboration, mobility and team diversity in the life sciences: Impact on research performance. *Social Geography*, *3*(1), 23–36.
Bauder, H. (2012). The international mobility of academics: a labour market perspective. International Migration.
Beaver, D., & Rosen, R. (1979). Studies in scientific collaboration part II. *Scientometrics*, *1*(2), 133–149.
Beckmann, K. & Schneider, A. (2011). The interaction of publications and appointments: New evidence on academic economists in germany. Education Economics pp. 1–16.
Bergman, E. (2011). Hirschmann mobility among academics of highly ranked eu research universities. ERSA conference papers ersa11p1134, European Regional Science Association.
Borjas, G.J., Doran, K.B. (2014). Which peers matter? The relative impacts of collaborators, colleagues, and competitors. NBER Working Papers 20026, National Bureau of Economic Research Inc.
Boschma, R. A. (2005). Does geographical proximity favour innovation? *Economie et Institutions*, *6*, 111–127.
Bosquet, C., Combes, P.P. (2013). Do large departments make academics more productive? Agglomeration and peer effects in research. SERC Discussion Papers (0133).
Breuninger, S. (2013). Mobilitaet und Karriereerfolg von Nachwuchswissenschaftlern. Unpublished manuscript.
Cañibano, C., Otamendi, J., & Andújar, I. (2008). Measuring and assessing researcher mobility from cv analysis: The case of the ramón y cajal programme in spain. *Research Evaluation*, *17*(1), 17–31.
Carayol, N. (2007). Academic incentives, research organization and patenting at a large french university. *Economics of Innovation and New Technologies*, *16*(2), 119–138.
Carayol, N., & Matt, M. (2006). Individual and collective determinants of academic scientists productivity. *Information Economics and Policy*, *18*(1), 55–72.
Cassiman, B. & Veugelers, R, (2002). R&D cooperation and spillovers: Some empirical evidence from belgium. American Economic Review pp. 1169–1184.
Cohen, W. M., & Levinthal, D. A. (1989). Innovation and learning: The two faces of R & D. *The Economic Journal*, *99*(397), 569–596.
Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*, 128–152.
Combes, P.P. & Linnemer, L. (2010). Inferring missing citations: A quantitative multi-criteria ranking of all journals in economics. Working Papers HAL 00520325.
Dietz, J. S., & Bozeman, B. (2005). Academic careers, patents, and productivity: Industry experience as scientific and technical human capital. *Research Policy*, *34*(3), 349–367.
Dubois, P., Rochet, J.C., Schlenker, J.M. (2012). Productivity and mobility in academic research: Evidence from mathematicians. Institut d'Économie Industrielle (IDEI), Toulouse.
Elhorst, J. P., & Zigova, K. (2014). Competition in research activity among economic departments: Evidence by negative spatial autocorrelation. *Geographical Analysis*, *46*(2), 104–125.
EU Commission (2000). Communication from the commission to the council, the european parliament, the economic and social committee and the committee of the regions: Towards a european research area.
EU Commission (2007). The European Research Area: New Perspectives.
Fabel, O., Hein, M., & Hofmeister, R. (2008). Research productivity in business economics: An investigation of Austrian, German and Swiss universities. *German Economic Review*, *9*(4), 506–531.
Fernandez-Zubieta, A., Geuna, A. & Lawson, C. (2013). Researchers' mobility and its impact on scientific productivity. University of Turin Working paper 2013(3).
Frank, R. (1985). *Choosing the right pond: Human behaviour and the quest for status*. New York: Oxford University Press.

Goyal, S., Van Der Leij, M. J., & Moraga-González, J. L. (2006). Economics: An emerging small world. *Journal of Political Economy*, *114*(2), 403–412.
Griffith, R., Lee, S., & Van Reenen, J. (2011). Is distance dying at last? Falling home bias in fixed-effects models of patent citations. *Quantitative economics*, *2*(2), 211–249.
Handelsblatt, (2011a). Journalliste. http://www.handelsblatt.com/politik/oekonomie/vwl-ranking/
Handelsblatt, (2011b). VWL-Ranking. http://www.handelsblatt.com/politik/oekonomie/vwl-ranking/methodik-so-funktioniert-das-vwl-ranking/4575334.html/
Hanushek, E. A., Kain, J. F., Markman, J. M., & Rivkin, S. G. (2003). Does peer ability affect student achievement? *Journal of Applied Econometrics*, *18*(5), 527–544.
Harzing, A. W. (2008). Arbitrary decisions in ranking studies: A commentary on Xu, Yalcinkaya, and Seggie. *Asia Pacific Journal of Management*, *25*(4), 685–689.
Hoch, P. K. (1987). Migration and the generation of new scientific ideas. *Minerva*, *25*(3), 209–237.
Hoisl, K. (2007). Tracing mobile inventors: The causality between inventor mobility and inventor productivity. *Research Policy*, *36*(5), 619–636.
Hoisl, K. (2009). Does mobility increase the productivity of inventors? *The Journal of Technology Transfer*, *34*(2), 212–225.
Jaffe, A. B., Trajtenberg, M., & Fogarty, M. S. (2000). Knowledge spillovers and patent citations: Evidence from a survey of inventors. *American Economic Review Papers and Proceedings*, *90*, 215–218.
Jonkers, K., & Tijssen, R. (2008). Chinese researchers returning home: Impacts of international mobility on research collaboration and scientific productivity. *Scientometrics*, *77*(2), 309–333.
Jovanovic, B. (1979). Job matching and the theory of turnover. *The Journal of Political Economy*, *87*(5), 972–990.
Katz, J. S., & Martin, B. R. (1997). What is research collaboration? *Research policy*, *26*(1), 1–18.
Kim, E. H., Morse, A., & Zingales, L. (2009). Are elite universities losing their competitive edge? *Journal of Financial Economics*, *93*(3), 353–381.
Laband, D. N., & Tollison, R. D. (2000). Intellectual collaboration. *Journal of Political Economy*, *108*(3), 632–662.
Leamer, E. E., & Storper, M. (2001). The economic geography of the internet age. *Journal of International Business Studies*, *32*(4), 641–665.
Lee, S., & Bozeman, B. (2005). The impact of research collaboration on scientific productivity. *Social Studies of Science*, *35*(5), 673–702.
Levin, S. G., & Stephan, P. E. (1991). Research productivity over the life cycle: Evidence for academic scientists. *American Economic Review*, *81*(1), 114–132.
Lotka, A. J. (1926). The frequency distribution of scientific productivity. *Journal of Washington Academy Sciences*, *16*, 317–323.
Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *Review of Economic Studies*, *60*(3), 531–42.
More, (2010). Mobility patterns and career paths of eu researchers. http://ec.europa.eu/euraxess/pdf/research_policies/MORE_final_report-_final_version
Polany, M. (1967). *The tacit dimension*. London: Routledge.
Ralph, K., & Bertrand, B. (2011). Critical mass and the dependency of research quality on group size? *Scientometrics*, *86*(2), 527–540.
Rauber, M., & Ursprung, H. (2008a). Evaluation of researchers: A life cycle analysis of german academic economists. In M. Albert, S. Voigt, & D. Schmidtchen (Eds.), *Conferences on new political economy, conferences on new political economy* (Vol. 25). Tuebingen: Mohr Siebeck.
Rauber, M., & Ursprung, H. W. (2008b). Life cycle and cohort productivity in economic research: The case of germany. *German Economic Review*, *9*, 431–456.
Rosenblat, T. S., & Möbius, M. M. (2004). Getting closer or drifting apart? *Quarterly Journal of Economics*, *119*(3), 971–1009.
Saisana, M., d'Hombres, B., & Saltelli, A. (2011). Rickety numbers: Volatility of university rankings and policy implications. *Research Policy*, *40*(1), 165–177.
Santos Silva, J., & Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, *88*(4), 641–658.
Scellato, G., Franzoni, C., & Stephan, P. (2012). Mobile scientists and international networks. National Bureau of Economic Research : Tech. rep.
Schankerman, M., Shalem, R. & Trajtenberg, M. (2006). Software patents, inventors and mobility. Unpublished manuscript.
Schubert, A., & Glänzel, W. (1983). Statistical reliability of comparisons based on the citation impact of scientific publications. *Scientometrics*, *5*(1), 59–73.

Seglen, P. O. (1997). Why the impact factor of journals should not be used for evaluating research. *BMJ British Medical Journal*, *314*(7079), 498.

Simmie, J. (2005). Critical surveys edited by stephen roper innovation and space: A critical review of the literature. *Regional Studies*, *39*(6), 789–804.

Sonn, J. W., & Storper, M. (2008). The increasing importance of geographical proximity in knowledge production: An analysis of us patent citations, 1975–1997. *Environment and Planning A*, *40*(5), 1020.

Stephan, P. (2012). *How economics shapes science*. Cambridge: harvard university press.

Stigler, G. J. (1988). *Memoirs of an unregulated economist*. New York: Basic Books.

Stoyanov, A., & Zubanov, N. (2012). Productivity spillovers across firms through worker mobility. *American Economic Journal: Applied Economics*, *4*(2), 168–198.

Swiss National Science Foundation (2014). Lead agency - Facilitating cross-border research http://www.snf.ch/en/funding/supplementary-measures/lead-agency/Pages/default.aspx

Teodorescu, D. (2000). Correlates of faculty publication productivity: A cross-national analysis. *Higher Education*, *39*(2), 201–222.

Thompson, P., & Fox-Kean, M. (2005). Patent citations and the geography of knowledge spillovers: A reassessment. *American Economic Review*, *95*(1), 450–460.

Topel, R. H., & Ward, M. P. (1992). Job mobility and the careers of young men. *The Quarterly Journal of Economics*, *107*(2), 439–479.

Trajtenberg, M. (2006). The mobility of inventors and the productivity of research. Unpublished manuscript.

Vigidor, J. & Nechyba, J. (2007). Schools and the equal opportunity problem, MIT Press, chap Peer Effects in North Carolina Public Schools.

Walckiers, A. (2008). Multi-dimensional contracts with task-specific productivity: An application to universities. *International Tax and Public Finance*, *15*(2), 165–198.

Waldinger, F. (2010). Quality matters: The expulsion of professors and the consequences for phd student outcomes in Nazi Germany. *Journal of Political Economy*, *118*(4), 787–831.

Waldinger, F. (2012). Peer effects in science: Evidence from the dismissal of scientists in Nazi Germany. *The Review of Economic Studies*, *79*(2), 838–861.

Weinberg BA (2006) Geography and innovation: Evidence from nobel laureate physicists. Proceedings of the Federal Reserve Bank of Cleveland.

Weitzman, M. L. (1998). Recombinant growth. *Quarterly Journal of Economics*, *113*(2), 331–360.

Wolf, J., Rohn, A.S. & Macharzina, K. (2006). Forschungsleistung in der deutschsprachigen Betriebswirtschaftslehre: Konzeption und Befunde einer empirischen Untersuchung. Springer DE.

Wuchty, S., Jones, B. F., & Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, *316*(5827), 1036–1039.