

Bolli, Thomas; Schläpfer, Jörg

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Job mobility, peer effects, and research productivity in economics

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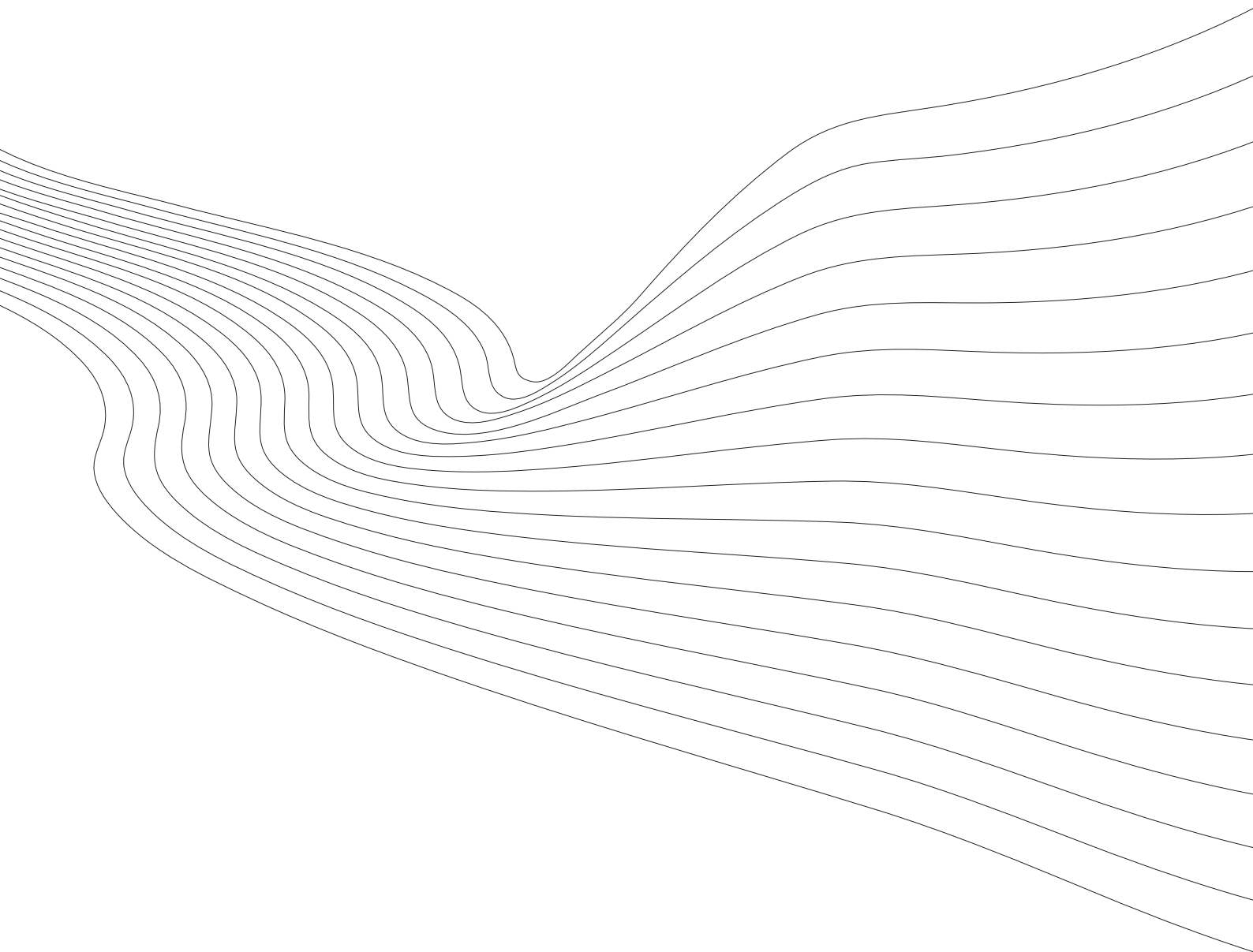
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KOF Working Papers

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Thomas Bolli, Jörg Schläpfer



KOF

ETH Zurich
KOF Swiss Economic Institute
WEH D 4
Weinbergstrasse 35
8092 Zurich
Switzerland

Phone +41 44 632 42 39
Fax +41 44 632 12 18
www.kof.ethz.ch
kof@kof.ethz.ch

Job Mobility, Peer Effects, and Research Productivity in Economics

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Thomas Bolli

`bolli@kof.ethz.ch`

Jörg Schläpfer

`schlaepfer@kof.ethz.ch`

KOF Swiss Economic Institute, Weinbergstrasse 35, 8092 Zürich, Switzerland

Abstract

Analysing a comprehensive panel dataset of economists working at Austrian, German, and Swiss universities, we investigate how the local environment influences a scientist's research productivity. The research environment varies if a scientist joins another department or if the characteristics of his colleagues change. We find no influence of the research environment on the average researcher's productivity, if we control for individual characteristics. This result indicates that with today's communication technologies spillovers are not bounded locally.

JEL classification: I23, J62.

Keywords: University, economics, productivity, mobility, peer effects, bibliometrics.

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1 Introduction

Kenneth Arrow stated in 1962 that “there is plenty of reason to suppose that the individual talents count for a good deal more than the firm as an organization“. Is this true? The source of an organization’s productivity may derive from the personal characteristics of its members or from the synergy effects that emerge if these members collaborate effectively and benefit from a well-designed organizational environment. Which of these contributing factors is more important depends on the organization’s characteristics and the available technology. In this study we explore the productivity of university scientists and ask in particular to what extent individual research productivity depends on individual factors, such as ability, as compared to local interactions.

A special role play scientists who switch jobs. It is generally believed that mobility increases the productivity of scientists. For that reason the EU has the European Research Area (ERA) initiated in the year 2000 (EU Commission, 2000). In order to reach its goal of fostering mobility, the European Network of Mobility Centres (ERA-MORE) and the Pan-European Researcher’s Mobility Web Portal (EURAXES) were set up and a number of smaller initiatives, such as the European Cooperation in Science and Technology (COST), were initiated. Moreover, the EU began to tackle legal and administrative obstacles of job mobility in the science system (EU Commission, 2007).

Yet, empirical studies so far suggest mixed correlations between academic mobility and research output. The causal impact of the pure moving effect (Bauder, 2012) on research productivity is unclear. Similarly, the existence of a peer effect has not unambiguously been established in a causal setting. While it is obvious that most if not all faculty members of prestigious university departments are productive researchers, it remains unclear whether top universities are successful in appointing inherently productive researchers or whether they excel in creating a research environment that is conducive to research.

To shed more light on this thorny issue of causality we make use of 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 to 2008.

To measure yearly productivity we count publications in refereed-journals and weight them by the quality of the journal and divide them by the number of authors. 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) or Dubois et al. (2012) and estimate a reduced form equation with Pooled Ordinary Least Squares (POLS) and - in order to tackle endogeneity from unobserved heterogeneity - in a Lagged Dependent Variable (LDV) and a Fixed Effect (FE) setting.

Our contribution is enhancing the causal interpretations by using an extensive database that covers the full map of economists working at universities in the German-speaking area. Thereby, we complement the existing literature which rather focuses on top researchers publishing in a more restricted list of journals. Our results suggest that on average moving does not have an impact on research output. Local peer effects appear as correlations, but when individual FE's are included in order to absorb unobserved heterogeneity, estimates of peer effects and the variables measuring matching quality lose their significance.

The findings support the literature suggesting that - the progress in communication technology - spillovers are not bounded locally. Dubois et al. (2012) do not find a peer effect either, and Kim et al. (2009) argue that peer effects have vanished over the last few decades. They explain the decrease of locality of spillovers in universities with the diminishing importance of local interaction due to the progress in information and travelling technology. As a consequence of ever more globally integrated research, knowledge can spill over between universities without explicitly hiring a researcher and thus, formally moving to another university is no prerequisite for fruitful exchanges among researchers. And indeed, researchers from loosely linked institutions collaborate more frequently resulting in increased co-authorships across universities (Laband and Tollison, 2000).

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

2 Literature and hypothesis

In this chapter we present three hypotheses and briefly summarize the underlying theoretical and empirical literature. The hypotheses state how individual research productivity relates to job mobility, interactions with peers and job matching at the workplace. Even though these hypotheses relate to different workplace characteristics, they overlap to some extent, because a move also conveys a new research environment.

Job mobility

Workers change their job, because they expect an increase in salary, a promotion, better working condition or a more pleasant living environment (Bergman, 2011). Academics are particularly attracted by reputational concerns, autonomy, access to research grants, and institutions that value their line of research (Ackers, 2005). Already in ancient Greece, scholars were more mobile than the population at large (Bauder, 2012). Nowadays, mobility is often perceived to be necessary for career progress (Ackers, 2005, Morano-Foadi, 2005). Switching jobs affects the productivity of the researcher in three ways: via new colleagues, the new institution and the match of an individual to his environment.

Moving exposes the researcher to the ideas of new colleagues (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). New colleagues provide additional tacit knowledge that is not published (Polany, 1967), thereby offering access to knowledge that is locally bounded.

Moving also alters the organisational environment. The new position may offer better access to resources and infrastructure. Furthermore, teaching obligations and administrative duties may also change (Teodorescu, 2000). Academics are especially keen on switching jobs if the new university provides them with more time for own projects (Wolf et al., 2006).

Matching theory suggests that a job change is generally associated with a better job match (Topel and Ward, 1992, Jovanovic, 1979), which, in turn, generally improves the productivity of the worker (Hoisl, 2009). In academia, a good job match facilitates the

acquisition of knowledge, in particular via collaboration and co-authorship. If the new university is characterized by a substantial group of researchers working in the same sub-field, then this effect is likely to be magnified (Azoulay et al., 2010). These arguments suggest:

Hypothesis 1: The research productivity of a researcher increases after having changed his job to a new university.

The available empirical evidence related to hypothesis 1 suggests mixed correlations between academic mobility and research output. Jonkers and Tijssen (2008) document that Chinese life scientists returning home from abroad increase their research output, but perhaps their gain of scientific human capital abroad might play a substantial role in addition to the selection effect. For Spain, Cañibano et al. (2008) find little evidence of a positive correlation between mobility and publication quantity. A study with a more causal setting by Dubois et al. (2012) suggests that a move slightly increases future research output. Another recent study by Fernandez-Zubieta et al. (2013), who analyse the publication record of 171 researchers in the UK, find no general impact of mobility on publication output. They find a positive impact only if the job changes occur to an institution with better reputation.

The patent literature, which draws on a longer tradition of analysing the influence of job mobility, has shown that inventors who change their employer are significantly and substantially more productive.¹ For example Hoisl (2007) uses an instrument in a simultaneous equation setting to control for a potential selection effect and also compares the pre-post performance with a control group (Hoisl, 2009). A positive association of job mobility is also confirmed in the studies by Latham et al. (2011) and Kim and Marschke (2005). Schankerman et al. (2006), on the other hand, do not find an effect of mobility in the software industry.

The mobility effect is perhaps more pronounced in the private sector than in academia,

¹Obtaining publications and patents are both high-skill knowledge processes, whose rewards are based on priority (Carayol, 2007), they have an identifiable creator and their individual value is frequently measured by citations (Dietz and Bozeman, 2005).

because firm boundaries, competitive markets and property rights prevent knowledge from flowing freely and spilling over across firms. In contrast, academic knowledge is generally non-proprietary; academics actually make sure that their output is publicised globally in order to gain reputation.

Even if job mobility does not improve the productivity of a researcher, he might generate an externality (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). An incoming researcher brings explicit and tacit knowledge into his new organization, from which organizations can benefit. A necessity for this effect is that local peer effects play a role.

Peer effects

Peer effects do not only materialize when an academic switches job, but they are always at work when people collaborate. Researchers with a large global network are more productive. The question at hand is whether there are peer effects that are bounded locally. We therefore test whether the productivity of a researcher is influenced by the productivity of the members of his department.

It is a stylized fact that the research productivity of the members of the same department are correlated, because more accomplished researchers generally work at universities with highly visible research output. The following question arises: Are universities with an outstanding reputation more successful at hiring productive researcher (selection effect) or does an excellent research environment provide synergy effects that magnify inherent ability (local peer effect) (Dubois et al., 2012)?

Peer effects depend on group dynamics such as group pressure, on the knowledge of peers and on spillover intensity. Peers can create a competitive environment, which motivates the members of the department to align their efforts. Moreover, the higher the ability of peers to produce research, the more you can learn from them and the more valuable feedback they can provide. Spillovers are knowledge flows from one unit to another unit (Dietz and

Bozeman, 2005) and are enhanced by the non-rival nature of academic knowledge (Jaffe et al., 2000). Yet, spillovers can be bounded locally so that they may be restricted to researchers from the same university. And exchanges of expertise or ideas are facilitated by the research activities of peers at the same university (Elhorst and Zigova, 2011). These arguments lead us to propose:

Hypothesis 2: An economists research productivity is positively influenced by the research productivity of the peers at the same university.

The empirical evidence about peer effects in academia is mixed. Some studies find a positive peer effect as formulated in our hypothesis. Allison and Long (1990) document a sizeable influence of the productivity of peers. Working at a more productive lab is associated with a substantial increase in individual performance and similarly, working at a less productive lab dampens personal output. They name three factors contributing to the department's impact: intellectual stimulation by colleagues; computer, library and laboratory facilities; as well as how much research is esteemed. A more recent study by Carayol and Matt (2006) confirm this finding for a sample of more than 1000 mostly natural scientists at the French Louis Pasteur University for the years 1993 to 2000.

For doctoral students, knowledge externalities are confirmed in a study by Waldinger (2010), who convincingly uses the expulsion of Jewish mathematician by the Nazi regime professors as an exogenous variation to the productivity of the faculty. His estimations suggests that a deterioration in faculty productivity by one standard deviation induces a significantly lower probability of publishing in a top journal by 13 percentage points. However, results from mentored doctoral students cannot readily be compared to peer effects on the level of professors, because senior researchers have established a broader network (Waldinger, 2010) and have accumulated more human capital. In a second study Waldinger (2012) used the same exogenous variation and finds no peer effect among the senior faculty.

A study by Kim et al. (2009) concludes that being affiliated with a top university had a positive causal effect on productivity in the 1970s, but this effect has vanished more

recently, due to lower cost and improved availability of communication across distances. While the causal effect of this location-specific component has vanished, top universities still attract researchers with high output. Recent findings from an exhaustive bibliometric database for mathematicians by Dubois et al. (2012) confirm that the local interaction effect is not important but that top universities are successful at hiring already productive researchers (selection effect). Improved distant communication loosens the dependence between a researcher and his colleagues at the same university. According to the model in Rosenblat and Möbius (2004) agents magnify the interaction with type-based groups if communication costs decrease. As a result, communities are rather fragmented in types than in geographic locations. And researchers worldwide are coming closer to each other. Exchanges across borders are everyday business in academia spanning an ever increasing network. (Goyal et al., 2006) The incidence of coauthorships among distant economists has been increasing progressively (Laband and Tollison, 2000). Scientific cooperation across universities are facilitated by English as the common academic language, lower cost of transport and communication and broader availability thereof, the increasing complexity and specialization of research, large scale multinational research programs (Jonkers and Tijssen, 2008, Katz and Martin, 1997) and frequent job moves (Cañibano et al., 2008).

The absence of peer effects at the university implies that knowledge spillovers are not bounded locally. And indeed, some studies using citation patterns for patents find that spillovers are at best modestly geographically bounded (Thompson and Fox-Kean, 2005), and that these bounds have been declining further over time with decreasing communication cost (Griffith et al., 2011). Other studies conclude that spillovers for patents are clearly bounded by national or state borders or metropolitan areas (Jaffe et al., 1993) respectively geographical separated job markets (Thompson, 2006). Zucker et al. (1998) present additional evidence of locally bounded spillovers in that the diffusion of human capital is the main determinant for where a high-technology industry developed. In general, measuring spillovers is challenging and, therefore, also testing whether spillovers are bounded locally is a challenging task (Thompson and Fox-Kean, 2005).

Matching with the faculty

To measure spillovers we rely on the most likely channels of transmitting knowledge at a university: namely working with co-authors and researchers working in overlapping sub-fields. After all, not every colleague is expected to generate the same spillovers, for example one can suppose that the most fruitful discussions are usually undertaken with researchers from the same sub-field because their feedback can be more targeted. Co-authors at the same institution are a social tie. Close proximity is essential if personal meetings are important, and to share tacit knowledge (Griffith et al., 2011). More and more research is undertaken in collaboration. In the social sciences the share of co-authored papers has increased from 20% to 50% in the last five decades. The incidence of co-operations has increased as a response to more division of labour and lower cost of communication (Wuchty et al., 2007) leading to the following hypothesis:

Hypothesis 3a: If two department members formally collaborate in joint research, their productivity will increase.

Since the number of researchers in a specific sub-field facilitates collaborative research, we use the share of department members working in the same sub-field as an indicator of the likelihood that productive knowledge spillovers occur:

Hypothesis 3b: The fraction of department members working in the same sub-field increases the productivity of the individual members.

If spillovers in academia are partially bounded locally, we would find a positive effect from co-authors and researchers on research productivity in the same sub-field at the same university - or proxies for measuring the transmission of spillovers. Hypothesis 3b would suggest that departments should specialise in order to publish more research. Specialisation, however, may have detrimental effects on the quality of teaching in some sub-fields (Rosenblat and Möbius, 2004). Hypothesis 3a is supported by a study for the medical research profession by Azoulay and Zivin (2005). They find that if a highly cited member of

a joint research project moves away, the research productivity of the remaining member decreases.

3 Sample

We analyse the influence of the research environment on research output. The dependent variable is quantified with a bibliometric measure, namely the quality weighted number of articles divided by the average number of authors per article. We consider the average of research output over a rolling window of two years and a time lag of two to three years.

Publications in refereed journals have substantial publication time lags, particularly in economics where editors ask for several revisions. Even though the exact lag between creation and publication remains unobserved for an individual publication, we need to identify the relevant time of the research process. 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). As a result, the average counts of articles published in $t + 2$ and $t + 3$ measures research output of the research process at time t .

Our dependent variable draws on the methodology of the Handelsblatt ranking 2011 - the most visible evaluation of the research output of economists and their departments in Austria, Germany and Switzerland (Handelsblatt, 2011b). The ranking is an assessment of publications in 1291 peer-reviewed journals - including all journals indexed by EconLit. Previous studies have mainly focused on top journals. 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. Analysing the full sample of economists at German-speaking universities allows to distinguish between researchers with high and low research output.

The relative weighting of the journals plays a crucial role. The most recent version of the Handelsblatt journal list for economists from the year 2011 allocates one of seven weights between 0.05 and 1 to 1291 peer-reviewed journals (Handelsblatt, 2011a). The weights are based on a study by Combes and Linnemer (2010), who estimate the quality of journals from which no impact factor exists. While research papers get full points, comments and replies earn half of the points, and editorials and chapters in book get no points. 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.

Allocating weights to individual publications based on the quality of the journal relies on the somewhat fragile assumption that a given journal quality weight is a good signal for the quality of an individual publication. Several bibliometric studies use citations instead of a journal weight to evaluate the quality of research based on the individual article instead of the journal. However, our empirical setting prevents us from employing this approach, because using citations would increase the time lag even further and hence sacrifice most the data, since an adequate assessment of citations requires several years of subsequent observations.

There is no perfect way of appropriately reflecting research productivity, also not with bibliometric methods. Yet, academic researchers, university administrators and their stakeholders widely use bibliometrics tools and indexes, and they are also used to analyse the research process (e.g. Stephan, 2012). Bibliometric evaluations ought to fulfil several quality criteria as outlined in Harzing (2008).

The Handelsblatt rankings are calculated at the KOF Swiss Economic Institute relying on the webportal *Forschungsmonitoring*. This platform has been initiated by the German Economic Association and also entails basic demographic characteristics, academic title and subfields of specialization. Due to the high visibility of the Handelsblatt ranking, researchers validate their publication data via a personal login in addition to manual administration and updates by the KOF Swiss Economic Institute. As a result, the accuracy of the data in

Forschungsmonitoring is higher than in many other non-relational bibliometric databases, which suffer for example from ambiguous spellings of researchers' names. For this study, we use this dataset, which covers all economists actively undertaking research at a university in Austria, Germany or the German-speaking part of Switzerland - three similar countries forming a common academic job market - between the years 2004 and 2008.

The Handelsblatt ranking of economists appeared in the years 2006, 2007, 2008, 2010 and 2011 and reveals the researcher's primary affiliation for these years. A faculty roster for the year 2004 published in Rauber and Ursprung (2006) complements the list of affiliations. Because our output variable refers to publications in $t+2$ and $t+3$ and mobility refers to movement between $t-1$ and t , our sample of economists refers to the years 2006, 2007 and 2008.

In principle, our sample represents the full population of research-active economists at 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 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. Note that the former group is a minority (Dubois et al., 2012) and the latter group typically ceased to publish in refereed journals.

We exclude emeriti from the sample and also drop 13 observations where getting tenured occurs together with a switch of universities (Rauber and Ursprung, 2008). After all, obtaining the first chair could induce endogeneity, because it is associated with a particular impact on research output. This sample restriction ensures that our mobility estimates are not driven by a correlation of mobility and a first call. By regulation, the first call is often associated with a university change in Germany. We drop departments with less than five researchers in the previous period (refer to e.g. Wolf et al., 2006) to ensure the consistency of our peer effect variables. Finally, we drop individuals with a single observation only. This leaves us with 498 economists at 48 universities.

4 Empirical strategy

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

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

In this three-way panel $y_{i,j_t,t}$ denotes the research productivity of individual i working at university j generated in year t , i.e. measured by articles published in the years $t+2$ and $t+3$. We index the affiliation to university j by a time index j_t , in order to illustrate the structure when using lagged variables as instruments in case researchers change affiliations. The constant is denoted by α_0 . The yearly time dummies α_t account for trends in publication behavior. Individual fixed effects, which are applied in some specifications, are denoted by α_i . The error term is indicated by $\epsilon_{i,t}$ and - following Dubois et al. (2012) - is assumed to be clustered by individuals but not by universities, because there is more explanatory power in individual than in institutional clusters. A causal interpretation requires the assumption that the residuals are mean independent from the main explanatory variables (Dubois et al., 2012) conditional on all the covariates.

One of the explanatory variable of primary interest is $Mobil_{i,t}$, a dummy variable indicating whether an economist moves permanently to another university in the German-speaking area between $t-1$ and t . We include three variables characterizing the research environment at a given university. The first, $\bar{y}_{-i,j_t,t-1}$, refers to the performance of the peers measured by the average research productivity of the economists at the same university j as individual i in year $t-1$ (see e.g. Waldinger, 2010 or Kim et al., 2009). The index $-i$ represents every economist at a given university except for individual $-i$. The average research output of the colleagues controls for the research environment in order to identify the pure mobility effect. At the same time, $\bar{y}_{-i,j_t,t-1}$ tests hypothesis 2, i.e. the impact of

the research environment on individual research productivity. Note that $\bar{y}_{-i,j_t,t-1}$ captures the research environment as a whole and does not measure the pure peer effect only, which would reflect the research productivity of colleagues independently of the characteristics of the university they work at such as the teaching load. Rather, $\bar{y}_{-i,j_t,t-1}$ measures research environment as a composed effect of the inherent research skills of the colleagues at their department, together with the pure institutional specific effect, for example reflecting how much resources a university allows to invest in research.²

Variation in $\bar{y}_{-i,j_t,t-1}$ stems from four sources: i) economist i changes university, so that his variable $Mobil_{i,t}$ indicates 1, ii) the faculty of university j_t changes iii) the research productivity of peers varies over time iv) the resources that are spent on research changes at a given university. The change in research environment is particularly pronounced for case i) because mobility changes the list of colleagues entirely.

The second characteristic of the research environment, $\overline{Field}_{-i,j_t,t-1}$, captures the share of peers that have at least one field in common with the researcher. Building on Rauber and Ursprung (2008) we distinguish seven fields, namely microeconomics, macroeconomics, public economics, econometrics, finance, other economics and business. Finally, $Coauthor_{i,j_{t-1},t-1}$ is a dummy variable that indicates whether the researcher works at year $t - 1$ with a co-author from the same university.

Contemporary peer characteristics are linked to individual i , because the individual i 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 peer characteristics of university j_t by one year and use the lagged values as instrument. This instrumenting approach rules out feedback effects from an individual researcher to his peers. It implies that peer characteristics, i.e. $\bar{y}_{-i,j_t,t-1}$, $\overline{Field}_{-i,j_t,t-1}$ and $Coauthor_{i,j_{t-1},t-1}$ to the lagged peer characteristics of individual i in case of no mobility. In the case of

²Our main interpretation from the coefficient of $\bar{y}_{-i,j_t,t-1}$ is the effect of the research environment measured by the output of peers. While this is of interest on its own, it would at the same time explain the pure peer effects independently of institution under either of the following assumptions. First, if institutional fixed effects are zero when controlling for the research output ability of colleagues. And if secondly, are independent of the residuals $\epsilon_{j,t}$.

mobility, peer characteristics refer to the average peer characteristics of university j_t at time $t-1$. For $Coauthor_{i,j_{t-1},t-1}$, being mobile means that the dummy variable takes the value 1 if one of the co-authors works at the same university j_{t-1} at time $t-1$.

Matrix $Z_{i,j_t,t-1}$ captures the institutional control variables. The number of economists per university (*Size*) enters in a quadratic form to account for potentially decreasing economies of scale (see, e.g., Fabel et al., 2008). The yearly fraction of the faculty at university j that has moved in from another university is denoted by $IncomingShare_{-i,j_t,t-1}$ and is used to control for differences in turnover frequencies across universities.

Matrix $X_{i,t}$ captures the individual control variables, namely the researcher's experience, gender and sub-field and whether his position is tenured. 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. In analogy to a Mincer type wage equation we control in a quadratic form for career age - defined as years since the Ph.D. thesis - and label it $Experience_{i,t}$. The first tenured position plays a particular role. While promotion reflects a selection effect and generally increases the resources (Carayol and Matt, 2006), research productivity usually declines after obtaining a permanent job, suggesting that extrinsic motivation plays an important role in the publication process (see Rauber and Ursprung, 2008 or Backes-Gellner and Schlinghoff, 2010). Hence, we include a dummy variable indicating whether a researcher has already received his first call ($Tenured_{i,t}$). We further observe the $Gender_i$ and the $Subfield_i$ of specialisation. While interpreting the estimated coefficients of these individual characteristics are interesting on their own, in this context their motivation is to serve as control variables for their effect on research productivity (Kim et al., 2009).

Table 1 lists the definition of the variables. All variables, including their squares but except for the dummy variables $Mobil_{i,t}$, $Coauthor_{i,j_{t-1},t-1}$ and $Tenured_{i,t}$, enter in logarithmic form in order to induce an elasticity setting. In the basic regression we enable the transformation of the 0's into logarithms by adding 0.01 for technical reasons.³ The descriptive statistics including variables means by country and gender are presented in

³Replacement values of 1, 0.1 and 0.001 yield qualitatively the same results.

Table 1: *Definitions of the dependent and independent variables*

y	Yearly publication output in $t + 2$ and $t + 3$, weighted by „Handelsblatt“ journal weights divided by number of authors
$Mobil$	Dummy variable that takes the value 1 if a researcher moved to a new university in the German-speaking area between $t - 1$ and t and 0 otherwise
\bar{y}_{-i}	One year lagged average output of peers at the university affiliation in t
\overline{Field}	One year lagged share of peers at the same university in t that share at least one field as the researcher i
$Coauthor$	One year lagged dummy variable that takes the value 1 if one of the co-authors of the researcher i shares his affiliation in $t - 1$ and 0 otherwise
$IncomingShare$	One year lagged share of peers moving to the university
$Size$	One year lagged number of research active employees at the university affiliation in $t - 1$
$Tenured$	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 male and 1 for female
$Subfield$	An economist i works in one or several of the following sub-fields: microeconomics, macroeconomics, public economics, econometrics, finance, business and other

table 2. The average research productivity is 0.19, the highest observed average research productivity is 0.40. We observe 59 job moves, most of them in Germany, the country with the majority of observations.

In a first step, we estimate the parameters of equation (1) by pooled OLS, neglecting individual dummies α_i . These columns are labelled POLS in the output tables, but their coefficients might suffer from a bias due to unobserved heterogeneity. For example $y_{i,t}$ could be correlated with the propensity to move or individual research ability is unobserved and correlated with the output of peers ($\bar{y}_{-i,j_t,t-1}$).

In a first attempt to capture unobserved heterogeneity we add a lagged dependent variable (LDV) to the right-hand side of equation (1). Building on the concept of adaptive expectation, LDV captures the research potential of economist i . Thereby, LDV serves as a proxy for research ability 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

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

Variable	Mean	Std. Dev.	Min	Max	Mean			Mean	
					AU	CH	DE	Male	Female
<i>y</i>	0.19	0.23	0	1.85	0.12	0.29	0.19	0.20	0.12
<i>Mobil</i>	0.05	0.21	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
<i>Field</i>	0.38	0.21	0	1	0.45	0.36	0.38	0.38	0.42
<i>Coauthor</i>	0.35	0.48	0	1	0.32	0.35	0.36	0.36	0.29
<i>IncomingShare</i>	0.11	0.15	0	1	0.03	0.20	0.11	0.11	0.11
<i>Size</i>	15.76	9.68	5	41	18.09	20.25	14.77	15.52	17.55
<i>Experience</i>	11.08	9.43	0	37	11.32	10.65	11.11	11.78	5.98
<i>Tenured</i>	0.92	0.28	0	1	0.96	0.94	0.91	0.92	0.93
<i>Gender</i>	0.12	0.32	0	1	0.20	0.08	0.11	0	1
<i>Micro</i>	0.35	0.48	0	1	0.43	0.35	0.33	0.33	0.49
<i>Macro</i>	0.33	0.47	0	1	0.39	0.405	0.31	0.34	0.22
<i>Public</i>	0.42	0.49	0	1	0.42	0.38	0.43	0.42	0.44
<i>Econometrics</i>	0.17	0.38	0	1	0.20	0.20	0.17	0.19	0.08
<i>Financece</i>	0.03	0.18	0	1	0.01	0.016	0.04	0.04	0
<i>Business</i>	0.012	0.11	0	1	0	0.02	0.013	0.01	0
<i>Other subfield</i>	0.06	0.24	0	1	0.12	0.08	0.05	0.06	0.09
N		1194			148	126	920	1051	143

the propensity to move across economists. We control for time constant unobserved heterogeneity in all explanatory variables by including individual dummy variables α_i (Kim et al., 2009, Dubois et al., 2012) and label the columns of these estimates FE. The assumption for unbiased estimates from POLS is extended by further conditioning on the α_i 's. Then, the assumption for unbiased FE estimates states that the residuals are mean independent from the explanatory variables conditional on all covariates including the individual dummy variables. Several reasons speak in favour of the plausibility of this assumption: Ability is generally recognized to be constant over time. We analyse research output over a period of four years of researchers that in 92% of the observations are already tenured. In addition, we drop observations with the special event of getting tenured and also control for experience. Furthermore, the exact timing of a move is more random than whether a researcher moves at all. The fairly time constant propensity to move is captured by the individual fixed effects (α_i).

The variables α_i and $\bar{y}_{-i,j_t,t-1}$ are crucial for identifying causal effects of mobility.⁴ They capture two possibly disturbing effects: i) Mobility could be driven by self-selection in two ways. Highly productive researchers are more likely to be offered a new job. Furthermore, top universities may have more changes in the composition of their faculty and their researchers might have a higher propensity to move. We proxy these characteristics by the variable $IncomingShare_{i,j_t,t-1}$. ii) Academics at the new university have a different research productivity. On the one hand because of university-specific characteristics as for example more resources and a lower teaching load. Moreover, the new colleagues have different research skills, which, via peer effects, may influence the productivity of the incoming researcher.⁵

To sum up, job mobility, individual heterogeneity, α_i and the productivity of the colleagues, $\bar{y}_{-i,j_t,t-1}$, are used to identify the influence of mobility on research productivity (Kim et al., 2009, Dubois et al., 2012). Moves to new universities are crucial events, because they drive both main explanatory variables: A change in the variable $Mobil_{i,t}$ and they strongly drive the variation in $\bar{y}_{-i,j_t,t-1}$, conveying to the research productivity of the new colleagues. The identification of $\bar{y}_{-i,j_t,t-1}$ requires α_i .

5 Results

The estimation results of equation (1) for the full sample are presented in the first three columns of table 3. In POLS the coefficient estimated for $Mobil$ is positive significant, thus there is a positive correlation between moving and research output, even when controlling for career age. The estimated coefficient of 0.329 indicates that researchers who move have

⁴Note that we cannot base our identification on spell fixed effects as suggested by Andrews et al. (2006), because combining individual and institutional control dummy variables capture the innovations that the variable $Mobil_{i,t}$ explains.

⁵At this stage the assumption is required that moves do typically not occur from a university offering a productive research environment but with low productive peers to a university with few resources offered for research having researchers with a high potential to publish. This assumption is plausible, because in general there is a positive correlation between the resources that are meant to be spent on research and the inherent ability of its researchers to publish.

a 39% higher research output than those who stay.⁶ The first column further confirms the expected positive and significant correlation between $\bar{y}_{-i,jt,t-1}$ and y_i, t , because productive researchers tend to work at universities where the other researchers are productive as well. A 10% increase in research output of the peers at the same department goes hand in hand with a 4.41% higher output of a researcher. These POLS estimates overstate the peer effects though, because the level of individual research productivity is driven by the ability to publish, which in turn is correlated with the level of research productivity of the peers at the same university $\bar{y}_{-i,jt,t-1}$.

A framework that controls for individual ability is better suited for a causal interpretation. With a LDV and FE, the explanatory power of the estimates increases. If individual research ability is taken into account using an LDV approach, the research environment loses most of its impact. When controlling for unobserved heterogeneity even stricter in the FE setting, the estimated coefficients for mobility and peer effects are no more unambiguously positive, and the coefficients are no more statistically significant. While this result of no peer effects contradicts studies for private patents such as (Thompson, 2006) or for the academic research output (Carayol and Matt, 2006, Bosquet and Combes, 2013, Allison and Long, 1990), it is in line with recent findings by Waldinger (2012), Dubois et al. (2012) and Kim et al. (2009).

The estimate on having a co-author at the same university is positive and statistically significant for POLS, which means that good researchers work with co-authors from their institution. Introducing fixed effects clearly weakens the evidence. The other indicator for the job match, \overline{Field} , shows mixed evidence. To sum up, the variables measuring quality of the match of researcher i with the university are not statistically significant with FE.

Based on these first estimates, Hypothesis 1,2 and 3 would be rejected at first sight. We do not find empirical evidence that mobility increases research output in general. And we do not find evidence that either the output of peers at the same department improve own output or that the job matching with the faculty has a causal impact on research output. These findings of no significant effect in turn “suggest that the research environment has

⁶39% = $\exp\{0.329\}-1$

no effect on individual productivity“ (Kim et al., 2009: 363).

Peer effects are not bound locally. The arguably explanation is the decreasing cost and better availability of distant communication as well as travelling (see e.g. Griffith et al., 2011) enabling to communicate productively with colleagues from other universities. Better communication means 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 occurred (Rosenblat and Möbius, 2004, Kim et al., 2009). A related explanation is the decreasing importance of the dimension of the physical infrastructure like a library. Unlike in natural sciences, where an institutional effect might be more important due to the need for expensive laboratories (Teodorescu, 2000), on-line libraries and cheap computer power resulted in sufficient coverage of infrastructure for calculations in economics - at least for the universities covered in our sample.

But if we look closer and distinguish between high productive and low productive researcher, some qualifications to the general statement above arise. The sample split between researchers with output above and below the median productivity complements the existing literature, whose focus is rather on a list of top researchers in a more restricted list of top journals (see e.g. Dubois et al., 2012).

The coefficient of estimating $Mobil_{i,t}$ is positive for the more productive researchers and negative for the less productive researchers. The p-value for the null hypothesis of equal effects is rejected at a 15%-significance level for FE. In POLS peer effects are positive for researchers with high and low output. With FE they are still positive for academics with higher research output, but insignificant. The FE peer effect is negative but insignificant for the lower productive researcher. The null hypothesis of equal effects is rejected at a 15%-significance level.

Table 3: Estimation results of the variables testing the hypothesis of determinants of research productivity

	Full Sample			Low Productivity			High Productivity		
	POLS	LDV	FE	POLS	LDV	FE	POLS	LDV	FE
<i>Mobil</i>	0.329** (0.157)	0.162 (0.109)	-0.036 (0.128)	0.224 (0.191)	0.185 (0.198)	-0.236 (0.272)	0.150 (0.116)	0.081 (0.089)	0.088 (0.148)
$\ln \bar{y}_{-i}$	0.441*** (0.107)	0.129* (0.068)	0.034 (0.155)	0.227** (0.111)	0.041 (0.098)	-0.140 (0.275)	0.112 (0.083)	0.094 (0.068)	0.243 (0.177)
$\ln \overline{Field}$	-0.115** (0.047)	-0.043 (0.029)	0.026 (0.065)	-0.089 (0.058)	-0.071 (0.050)	0.043 (0.096)	0.034 (0.036)	0.036 (0.028)	-0.032 (0.087)
<i>Coauthor</i>	0.607*** (0.086)	0.074 (0.060)	0.057 (0.111)	0.455*** (0.099)	0.212** (0.091)	0.133 (0.170)	0.189** (0.075)	0.013 (0.059)	-0.039 (0.151)
<i>LDV</i>		0.657*** (0.028)			0.364*** (0.042)			0.386*** (0.039)	
$\alpha_t, X_{i,t}, Z_{i,j,t,t-1}$	YES	YES	YES	YES	YES	YES	YES	YES	YES
α_i	NO	NO	YES	NO	NO	YES	NO	NO	YES
N	1194	1194	1194	591	591	591	603	603	603
Adjusted R^2	0.134	0.470	0.643	0.052	0.171	0.292	0.040	0.228	0.278

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 journal quality and 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 the full sample and a split of the sample into researchers with above and below median research output. 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 0.67, 0.63 and 0.14 for *Mobil* and 0.39, 0.67 and 0.11 for \bar{y}_{-i} .

The statistical evidence for the distinction high versus low is relatively weak. But the impression holds for various specifications and thus all together paints a coherent picture of the following interpretation: Researchers with higher output seem to benefit more from mobility and from peer effects than lower productive researchers, even after controlling for individual fixed effects. This finding is in line with a positive impact of a move suggested by Dubois et al. (2012) for high level mathematicians. In the spirit of the literature about absorptive capacity (Cohen and Levinthal, 1990) high level researchers might be better able to get inspired from new and productive colleagues and to use their ideas for further improvements on their publication record. The finding of absorptive capacity is no contradiction to the two studies of Waldinger, who finds peer effects for researchers with relative low research output (doctoral students), but not for researchers with relative high output (professors). After all, while the peer effects in Waldinger (2012) capture mentoring, which is more urgent for doctoral students than for professors, our peer effect story is about the impact of good research of peers on research output of tenured academics.

A possible interpretation is that high level researchers change universities, because they aim at hitting the ground in research after a move and a new position - which is possibly even better suited for research - boosts their motivation. On the other hand, academics with a below average research productivity might move rather for personal reasons. This might include family reasons or new perspectives on the job, possibly with a shift from research to teaching or management. Thus, moving reflects a personal decision. However, motivation and effort change only slowly over time, hence our FE approach should capture this difference.

In Appendix B we present results for other specifications, showing that our results are relatively robust to excluding the observations with zero output and to multicollinearity.

6 Discussion

The results presented in the previous section indicate that research environment matters on average little for research productivity. While we show empirical evidence supporting this claim, we do not prove that the research environment is not pivotal for research output. Nonetheless, cooperation is a necessity in research. On the one hand this means working with co-authors in order to recombine ideas and to specialize, and on the other hand being well connected and getting feedback from colleagues as well as having inspiring talks with them. (Laband and Tollison, 2000, Stigler, 1988) But these comments are not necessarily made by peers at the same university, nowadays colleagues anywhere across the world can easily do so. 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).

Given that this study finds no positive impact of peers and the research environment on research output, it is not much of a surprise that, on aggregate, there are no positive effects from moving to another university. After all, parts of the expected gains from a job move are getting connected to more productive peers or to those with a better fit.

Even though our study suggests that moving to another university does not lead to higher publication output, moving has an impact on the network of co-authorships (Cañibano et al., 2008; Scellato et al., 2012) and it might increase the reputation and the visibility of a researcher and therefore also the career prospect (Bauder, 2012). And increase the network is an important part of academic job mobility (Ackers, 2005). The study about mobility and career paths of EU researchers (MORE, 2010) concludes that for academics the direct effect of their move on research productivity is less important than their impact on extending their network. While the job market value of an academic generally increases with a move, this increase often is the motivation to move in the first place.

Based on the positive impact from short term research visits abroad on research productivity as reported in Breuninger (2013) and supporting the view of Bauder (2012), a

policy suggestion from our study is that the academic system supports networks and grants also with a focus on short term mobility in addition to promote pure job rotation. Funds that foster cooperation via conferences (Weinberg, 2006) or on a project base are also beneficial. To some extent, project-wise collaborations across universities, conferences, and regular correspondence are substitutes for changing the faculty to match with appropriate peers and, thereby, contribute to the irrelevance of peer effects at the same university (Waldinger, 2012).

An ideal analysis distinguishes formal collaboration e.g. by publishing together from more informal sharing of thoughts, for example over coffee. but while the informal cooperation might well be beneficial, it is hard to measure.

In contrast to the findings in the literature about patents in private companies, we have not found a general effect of permanent job mobility on research output. But for academia human capital is more readily available for the public than it is the case in the private sector with the boundaries of competitive firms. Mobility in academia differs from mobility in other sectors (Bauder, 2012), because the academic labour market is particularly mobile, highly skilled and international (Ackers, 2005). Consequently, also the relation between mobility and productivity might be different from academia to other sectors. Nonetheless, the academic job market itself is relevant, because it measures relatively precisely the individual performance in a highly skilled sector (Kim et al., 2009: 354) and the existence of knowledge spillovers lie at the heart of the endogenous growth literature. Furthermore, taxpayers and other funders of universities have the right to know what research environment is best to achieve cutting-edge research, and the pressure to demonstrate the impact from funding increases (Kern, 2011).

References

- Ackers, L. (2005). Moving people and knowledge: Scientific mobility in the european union. *International Migration*, 43(5):99–131.
- Allison, P. D. and Long, J. S. (1990). Departmental effects on scientific productivity. *American Sociological Review*, 8:469–478.
- Andrews, M., Schank, T., and Upward, R. (2006). Practical fixed-effects estimation methods for the three-way error-components model. *Stata Journal*, 6(4):461–481.
- Azoulay, P., Graff Zivin, J., and Wang, J. (2010). Superstar extinction. *Quarterly Journal of Economics*, 25:549–589.
- Azoulay, P. and Zivin, J. G. (2005). The increasing dominance of teams in production of knowledge. *Working Paper, Columbia University*.
- Backes-Gellner, U. and Schlinghoff, A. (2010). Career incentives and publish or perish in german and us universities. *European Education*, 42(3):26–52.
- Barjak, F. and 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*.
- Beckmann, K. and Schneider, A. (2011). The interaction of publications and appointments: new evidence on academic economists in germany. *Education Economics*, pages 1–16.
- Bosquet, C. and 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., and 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. and Matt, M. (2006). Individual and collective determinants of academic scientists productivity. *Information Economics and Policy*, 18(1):55–72.
- Cohen, W. M. and Levinthal, D. A. (1990). Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly*, 35:128–152.
- Combes, P.-P. and Linnemer, L. (2010). Inferring missing citations: A quantitative multi-criteria ranking of all journals in economics. Working papers.
- Dietz, J. S. and 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., and Schlenker, J.-M. (2012). Productivity and mobility in academic research: Evidence from mathematicians. *Institut d'Économie Industrielle (IDEI), Toulouse*.
- Elhorst, J. P. and Zigova, K. (2011). Evidence of competition in research activity among economic department using spatial econometric techniques. *Department of Economics, University of Konstanz*.
- 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., and 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., and Lawson, C. (2013). Researchers' mobility and its impact on scientific productivity. *University of Turin Working paper*, 2013(3).
- Goyal, S., Van Der Leij, M. J., and Moraga-González, J. L. (2006). Economics: An emerging small world. *Journal of Political Economy*, 114(2):403–412.
- Griffith, R., Lee, S., and 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/>.
- Hanushek, E. A., Kain, J. F., Markman, J. M., and 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 (2008). *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., and Fogarty, M. S. (2000). Knowledge spillovers and patent citations: Evidence from a survey of inventors. *American Economic Review Papers and Proceedings*, 90:215–218.
- Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, 108(3):577–598.
- Jonkers, K. and 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. and Martin, B. R. (1997). What is research collaboration? *Research policy*, 26(1):1–18.
- Kern, S. (2011). Analytic model for academic research productivity having factors, interactions and implications. *Cancer Biology & Therapy*, 12(11):949–956.
- Kim, E. H., Morse, A., and Zingales, L. (2009). Are elite universities losing their competitive edge? *Journal of Financial Economics*, 93(3):353–381.
- Kim, J. and Marschke, G. (2005). Labor mobility of scientists, technological diffusion, and the firm’s patenting decision. *RAND Journal of Economics*, 36(2):298–317.
- Laband, D. N. and Tollison, R. D. (2000). Intellectual collaboration. *Journal of Political Economy*, 108(3):632–662.
- Latham, W., Le Bas, C., and Volodin, D. (2011). Value of invention, prolific inventor productivity and mobility: evidence from five countries, 1975-2002. *GATE Working Paper*.

- Levin, S. G. and Stephan, P. E. (1991). Research productivity over the life cycle: Evidence for academic scientists. *American Economic Review*, 81(1):114–132.
- Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *Review of Economic Studies*, 60(3):531–42.
- Morano-Foadi, S. (2005). Scientific mobility, career progression, and excellence in the european research area¹. *International migration*, 43(5):133–162.
- MORE (2010). Mobility patterns and career paths of eu researchers.
- Polany, M. (1967). *The Tacit Dimension*. London: Routledge.
- Rauber, M. and Ursprung, H. W. (2006). Evaluation of researchers: a life cycle analysis of german academic economists. Technical report, CESifo working papers.
- Rauber, M. and Ursprung, H. W. (2008). Life cycle and cohort productivity in economic research: the case of germany. *German Economic Review*, 9(4):431–456.
- Rosenblat, T. S. and Möbius, M. M. (2004). Getting closer or drifting apart? *Quarterly Journal of Economics*, 119(3):971–1009.
- Santos Silva, J. and Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, 88(4):641–658.
- Scellato, G., Franzoni, C., and Stephan, P. (2012). Mobile scientists and international networks. Technical report, National Bureau of Economic Research.
- Schankerman, M., Shalem, R., and Trajtenberg, M. (2006). Software patents, inventors and mobility. *Unpublished manuscript*.
- Stephan, P. (2012). *How Economics Shapes Science*. Harvard University Press.
- Stigler, G. J. (1988). *Memoirs of an Unregulated Economist*. New York: Basic Books.

- Teodorescu, D. (2000). Correlates of faculty publication productivity: A cross-national analysis. *Higher Education*, 39(2):201–222.
- Thompson, P. (2006). Patent citations and the geography of knowledge spillovers: evidence from inventor-and examiner-added citations. *The Review of Economics and Statistics*, 88(2):383–388.
- Thompson, P. and Fox-Kean, M. (2005). Patent citations and the geography of knowledge spillovers: A reassessment. *American Economic Review*, 95(1):450–460.
- Topel, R. H. and 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*.
- Vigdor, J. and Nechyba, J. (2007). *Schools and the Equal Opportunity Problem*, chapter Peer Effects in North Carolina Public Schools. MIT Press.
- 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, B. A. (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., and Macharzina, K. (2006). *Forschungsleistung in der deutschsprachigen Betriebswirtschaftslehre: Konzeption und Befunde einer empirischen Untersuchung*. Springer DE.

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

Zucker, L. G., Darby, M. R., and Brewer, M. B. (1998). Intellectual human capital and the birth of us biotechnology enterprises. *American Economic Review*, 88(1):290–306.

7 Appendix

Appendix A: Estimation results of all explanatory variables

In order to focus on the three hypothesis, in the chapter “Results” only the estimated coefficients of the main variables are shown. Table 4 reports the estimated coefficients of all other covariates as well.

Table 4: *Estimation results of research output for all covariates*

	Full Sample			Low Productivity			High Productivity		
	POLS	LDV	FE	POLS	LDV	FE	POLS	LDV	FE
<i>Mobil</i>	0.329** (0.157)	0.162 (0.109)	-0.036 (0.128)	0.224 (0.191)	0.185 (0.198)	-0.236 (0.272)	0.150 (0.116)	0.081 (0.089)	0.088 (0.148)
$\ln \bar{y}_{-i}$	0.441*** (0.107)	0.129* (0.068)	0.034 (0.155)	0.227** (0.111)	0.041 (0.098)	-0.140 (0.275)	0.112 (0.083)	0.094 (0.068)	0.243 (0.177)
$\ln \overline{Field}$	-0.115** (0.047)	-0.043 (0.029)	0.026 (0.065)	-0.089 (0.058)	-0.071 (0.050)	0.043 (0.096)	0.034 (0.036)	0.036 (0.028)	-0.032 (0.087)
<i>Coauthor</i>	0.607*** (0.086)	0.074 (0.060)	0.057 (0.111)	0.455*** (0.099)	0.212** (0.091)	0.133 (0.170)	0.189** (0.075)	0.013 (0.059)	-0.039 (0.151)
<i>IncomingShare</i>	0.046* (0.025)	0.023 (0.018)	-0.005 (0.031)	-0.009 (0.032)	0.003 (0.029)	-0.013 (0.054)	0.041* (0.023)	0.020 (0.019)	0.017 (0.036)
<i>Size</i>	-0.440 (0.559)	-0.393 (0.413)	-0.475 (0.716)	0.233 (0.677)	0.139 (0.622)	0.042 (1.224)	-0.334 (0.503)	-0.392 (0.439)	-0.521 (0.802)
<i>Size</i> ²	0.114 (0.108)	0.101 (0.079)	0.101 (0.138)	-0.059 (0.130)	-0.032 (0.121)	-0.025 (0.244)	0.065 (0.095)	0.081 (0.084)	0.107 (0.157)
<i>Experience</i>	-0.000 (0.025)	-0.026* (0.015)	0.177 (0.306)	0.004 (0.024)	0.019 (0.019)	0.141 (0.515)	-0.000 (0.022)	-0.030* (0.016)	0.172 (0.354)
<i>Experience</i> ²	-0.022** (0.010)	-0.008 (0.006)	0.026 (0.062)	-0.009 (0.009)	-0.005 (0.008)	0.028 (0.106)	-0.006 (0.008)	-0.003 (0.006)	0.017 (0.070)
<i>Tenured</i>	-0.268* (0.148)	-0.143 (0.097)	0.273 (0.321)	-0.096 (0.228)	-0.025 (0.194)	-0.064 (0.207)	0.104 (0.111)	0.068 (0.084)	0.352 (0.391)
<i>Gender</i>	-0.320** (0.137)	-0.077 (0.092)		-0.066 (0.139)	-0.005 (0.119)		-0.292*** (0.095)	-0.130 (0.085)	
<i>Micro</i>	0.173 (0.110)	0.120* (0.070)		0.024 (0.119)	0.054 (0.097)		-0.037 (0.088)	-0.030 (0.070)	
<i>Macro</i>	0.087 (0.114)	0.083 (0.070)		0.166 (0.121)	0.171* (0.097)		-0.026 (0.098)	-0.026 (0.077)	
<i>Public</i>	0.178 (0.108)	0.101 (0.068)		0.227* (0.118)	0.177* (0.099)		-0.003 (0.086)	-0.005 (0.065)	
<i>Econometrics</i>	-0.089 (0.127)	0.089 (0.077)		0.137 (0.139)	0.185 (0.113)		-0.209** (0.087)	-0.093 (0.070)	
<i>Finance</i>	0.500* (0.293)	0.383*** (0.136)		0.042 (0.310)	0.182 (0.196)		0.111 (0.230)	0.164 (0.138)	
<i>Business</i>	0.251 (0.523)	0.136 (0.290)		-0.671** (0.321)	-0.593*** (0.206)		0.299 (0.230)	0.216 (0.159)	
<i>Othersub – fiel</i>	-0.097 (0.187)	0.013 (0.103)		0.104 (0.188)	0.161 (0.135)		-0.002 (0.141)	0.037 (0.125)	
<i>Constant</i>	-1.093 (0.778)	-0.212 (0.574)	-3.500* (1.879)	-3.042*** (0.941)	-2.187** (0.859)	-4.844 (4.521)	-0.840 (0.685)	-0.031 (0.601)	-0.072 (1.280)
<i>LDV</i>		0.657*** (0.028)			0.364*** (0.042)			0.386*** (0.039)	
α_t	YES	YES	YES	YES	YES	YES	YES	YES	YES
α_i	NO	NO	YES	NO	NO	YES	NO	NO	YES
N	1194	1194	1194	591	591	591	603	603	603
R^2	0.149	0.479	0.795	0.084	0.200	0.609	0.072	0.255	0.585
Adjusted R^2	0.134	0.470	0.643	0.052	0.171	0.292	0.040	0.228	0.278

Table 4 shows OLS coefficients and robust standard errors clustered at individual level in parentheses.

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

The dependent variable is the Logarithms of the number of publications, weighted by journal quality and 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 2008-2011.

Appendix B: Robustness

Our sample contains a spike of observations 175 or about 13% of the sample with $y_{it}=0$, which is a rather low fraction for bibliometric standards. One reason for the relatively few observations with zero output lies in the aggregation of the dependent variable over two years. Additionally, the large set of 1291 journals increases the odds that a researcher publishes in one of these journals in any two year period. Furthermore, Handelsblatt considers only researchers which are meant to publish in refereed journals ignoring for example deans and honorary professors.

In order to verify that the observations with zero research output do not drive our results, table 5 displays estimates in which we drop these observations.

A further robustness test deals with multicollinearity. Our paper is about the impact of mobility and peer quality effects on research productivity. While equation (1) includes them simultaneously, table 6 shows results that consider these variables one after the other and with an interaction term. This allows analysing the separate impact of the two central dimensions of our paper, solves multicollinearity and accounts for the fact that large parts of variation in \bar{y}_{-i} comes from economists that change university.

The next two tables indicate that our results are relatively robust to excluding the observations with $y_{it}=0$ and to multicollinearity of the main explanatory variables.

Table 5: Robustness of results from table 3 without observations with 0 output

	Full Sample			Low Productivity			High Productivity		
	POLS	LDV	FE	POLS	LDV	FE	POLS	LDV	FE
<i>Mobil</i>	0.181 (0.135)	0.082 (0.088)	0.037 (0.126)	-0.054 (0.121)	-0.030 (0.117)	-0.175 (0.262)	0.116 (0.112)	0.050 (0.086)	0.126 (0.138)
$\ln \bar{y}_i$	0.367*** (0.090)	0.129** (0.057)	0.135 (0.126)	0.244*** (0.090)	0.102 (0.078)	0.218 (0.227)	0.095 (0.071)	0.077 (0.058)	0.145 (0.153)
$\ln \overline{Field}$	-0.069* (0.038)	-0.026 (0.024)	0.009 (0.051)	-0.049 (0.044)	-0.042 (0.038)	0.058 (0.074)	0.027 (0.034)	0.027 (0.026)	-0.049 (0.072)
<i>Coauthor</i>	0.306*** (0.072)	-0.062 (0.048)	-0.092 (0.084)	0.101 (0.075)	-0.052 (0.067)	-0.070 (0.131)	0.133** (0.064)	-0.027 (0.050)	-0.100 (0.109)
<i>IncomingShare</i>	0.038* (0.022)	0.017 (0.016)	-0.014 (0.024)	-0.009 (0.023)	-0.001 (0.022)	-0.007 (0.038)	0.034* (0.020)	0.015 (0.017)	-0.006 (0.030)
<i>Size</i>	0.143 (0.454)	0.081 (0.319)	-0.106 (0.568)	0.497 (0.537)	0.370 (0.472)	0.441 (0.977)	0.127 (0.431)	0.077 (0.367)	-0.107 (0.695)
<i>Size</i> ²	-0.005 (0.088)	0.004 (0.061)	0.049 (0.108)	-0.107 (0.105)	-0.077 (0.093)	-0.093 (0.195)	-0.020 (0.081)	-0.005 (0.069)	0.051 (0.131)
<i>Experience</i>	-0.005 (0.022)	-0.028** (0.014)	0.050 (0.222)	-0.004 (0.021)	-0.010 (0.018)	0.059 (0.329)	-0.009 (0.020)	-0.035** (0.015)	0.060 (0.297)
<i>Experience</i> ²	-0.015* (0.008)	-0.005 (0.005)	0.002 (0.047)	-0.005 (0.008)	-0.003 (0.007)	0.004 (0.071)	-0.006 (0.007)	-0.004 (0.006)	0.002 (0.061)
<i>Tenured</i>	-0.097 (0.131)	-0.048 (0.093)	0.263 (0.325)	0.119 (0.212)	0.139 (0.192)	-0.278 (0.174)	0.111 (0.103)	0.068 (0.084)	0.367 (0.375)
<i>Gender</i>	-0.251** (0.107)	-0.026 (0.075)		0.006 (0.112)	0.073 (0.094)		-0.304*** (0.079)	-0.142* (0.076)	
<i>Micro</i>	0.144 (0.090)	0.112* (0.059)		0.067 (0.089)	0.090 (0.075)		-0.026 (0.079)	-0.014 (0.061)	
<i>Macro</i>	-0.057 (0.098)	-0.019 (0.063)		-0.074 (0.096)	-0.053 (0.081)		0.011 (0.095)	0.009 (0.072)	
<i>Public</i>	0.039 (0.090)	0.007 (0.060)		0.099 (0.095)	0.065 (0.081)		-0.070 (0.082)	-0.064 (0.062)	
<i>Econometrics</i>	-0.159 (0.110)	0.006 (0.072)		0.012 (0.122)	0.056 (0.105)		-0.183** (0.080)	-0.076 (0.063)	
<i>Finance</i>	0.474** (0.234)	0.361** (0.143)		0.285* (0.167)	0.354* (0.196)		0.156 (0.210)	0.186 (0.139)	
<i>Business</i>	0.265 (0.424)	0.162 (0.248)		-1.148*** (0.193)	-0.983*** (0.212)		0.263 (0.251)	0.186 (0.177)	
<i>Othersub – field</i>	-0.129 (0.166)	-0.083 (0.103)		-0.068 (0.140)	-0.056 (0.108)		-0.013 (0.139)	0.022 (0.124)	
<i>LDV</i>		0.544*** (0.025)			0.272*** (0.035)			0.366*** (0.036)	
<i>Constant</i>	-1.440** (0.622)	-0.654 (0.446)	-2.690*** (0.958)	-2.863*** (0.784)	-2.182*** (0.705)	-1.967 (3.321)	-1.364** (0.591)	-0.612 (0.514)	-0.025 (2.126)
α_t	YES	YES	YES	YES	YES	YES	YES	YES	YES
α_i	NO	NO	YES	NO	NO	YES	NO	NO	YES
N	1040	1040	1040	446	446	446	594	594	594
R^2	0.122	0.486	0.845	0.066	0.198	0.735	0.077	0.298	0.663
Adjusted R^2	0.105	0.475	0.710	0.022	0.158	0.429	0.044	0.273	0.406

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 is the Logarithms of the number of publications, weighted by journal quality and number of authors in the years 2008-2011.

Estimates are shown for the full sample and a split of the sample into researchers with above and below median research output.

Table 6: Robustness of results from table 3 to multicollinearity

	POLS				LDV				FE			
	<i>Mobil</i>	\bar{y}_{-i}	Both	Interaction	<i>Mobil</i>	\bar{y}_{-i}	Both	Interaction	<i>Mobil</i>	\bar{y}_{-i}	Both	Interaction
<i>Mobil</i>	0.369** (0.154)		0.329** (0.157)	-0.478 (0.563)	0.171 (0.109)		0.162 (0.109)	-0.336 (0.353)	-0.035 (0.128)		-0.036 (0.128)	-0.119 (0.380)
$\ln \bar{y}_{-i}$		0.450*** (0.107)	0.441*** (0.107)	0.463*** (0.109)		0.132* (0.068)	0.129* (0.068)	0.142** (0.069)		0.033 (0.155)	0.034 (0.155)	0.037 (0.158)
<i>Mobil</i> * \bar{y}_{-i}				-0.475 (0.339)				-0.293 (0.188)				-0.049 (0.215)
$\ln \overline{Field}$	-0.119** (0.047)	-0.112** (0.047)	-0.115** (0.047)	-0.115** (0.047)	-0.043 (0.029)	-0.041 (0.029)	-0.043 (0.029)	-0.043 (0.029)	0.025 (0.065)	0.025 (0.064)	0.026 (0.065)	0.026 (0.065)
<i>Coauthor</i>	0.624*** (0.087)	0.601*** (0.086)	0.607*** (0.086)	0.605*** (0.086)	0.073 (0.060)	0.070 (0.060)	0.074 (0.060)	0.074 (0.060)	0.058 (0.111)	0.058 (0.111)	0.057 (0.111)	0.057 (0.111)
<i>IncomingShare</i>	0.075*** (0.025)	0.054** (0.025)	0.046* (0.025)	0.045* (0.025)	0.031* (0.019)	0.026 (0.018)	0.023 (0.018)	0.022 (0.019)	-0.006 (0.031)	-0.006 (0.030)	-0.005 (0.031)	-0.005 (0.031)
<i>Size</i>	-0.085 (0.561)	-0.447 (0.559)	-0.440 (0.559)	-0.412 (0.559)	-0.292 (0.405)	-0.396 (0.413)	-0.393 (0.413)	-0.376 (0.413)	-0.456 (0.715)	-0.470 (0.715)	-0.475 (0.716)	-0.471 (0.717)
<i>Size</i> ²	0.073 (0.108)	0.113 (0.107)	0.114 (0.108)	0.109 (0.107)	0.089 (0.078)	0.100 (0.079)	0.101 (0.079)	0.098 (0.079)	0.098 (0.138)	0.100 (0.138)	0.101 (0.138)	0.100 (0.138)
<i>Experience</i>	-0.002 (0.026)	-0.004 (0.025)	-0.000 (0.025)	-0.001 (0.026)	-0.027* (0.015)	-0.028* (0.015)	-0.026* (0.015)	-0.026* (0.015)	0.178 (0.306)	0.180 (0.305)	0.177 (0.306)	0.179 (0.307)
<i>Experience</i> ²	-0.021** (0.010)	-0.024*** (0.009)	-0.022** (0.010)	-0.022** (0.010)	-0.007 (0.006)	-0.009 (0.006)	-0.008 (0.006)	-0.008 (0.006)	0.026 (0.062)	0.026 (0.061)	0.026 (0.062)	0.026 (0.062)
<i>Tenured</i>	-0.312** (0.149)	-0.254* (0.149)	-0.268* (0.148)	-0.271* (0.148)	-0.154 (0.097)	-0.136 (0.098)	-0.143 (0.097)	-0.145 (0.098)	0.269 (0.320)	0.272 (0.321)	0.273 (0.321)	0.273 (0.321)
<i>Gender</i>	-0.343** (0.136)	-0.321** (0.138)	-0.320** (0.137)	-0.322** (0.137)	-0.081 (0.092)	-0.078 (0.092)	-0.077 (0.092)	-0.079 (0.092)				
<i>Micro</i>	0.151 (0.111)	0.180 (0.110)	0.173 (0.110)	0.173 (0.110)	0.113 (0.070)	0.124* (0.070)	0.120* (0.070)	0.120* (0.070)				
<i>Macro</i>	0.088 (0.117)	0.088 (0.115)	0.087 (0.114)	0.090 (0.114)	0.084 (0.070)	0.083 (0.070)	0.083 (0.070)	0.085 (0.070)				
<i>Public</i>	0.158 (0.111)	0.185* (0.108)	0.178 (0.108)	0.176 (0.108)	0.094 (0.068)	0.104 (0.068)	0.101 (0.068)	0.100 (0.068)				
<i>Econ</i>	-0.114 (0.130)	-0.091 (0.128)	-0.089 (0.127)	-0.086 (0.128)	0.084 (0.078)	0.089 (0.078)	0.089 (0.077)	0.091 (0.078)				
<i>Finance</i>	0.429 (0.284)	0.488* (0.293)	0.500* (0.293)	0.509* (0.293)	0.362*** (0.136)	0.377*** (0.136)	0.383*** (0.136)	0.389*** (0.136)				
<i>Business</i>	0.303 (0.546)	0.232 (0.524)	0.251 (0.523)	0.248 (0.520)	0.149 (0.520)	0.126 (0.292)	0.136 (0.290)	0.134 (0.289)				
<i>Othersub – field</i>	-0.127 (0.186)	-0.101 (0.187)	-0.097 (0.187)	-0.090 (0.188)	0.005 (0.101)	0.011 (0.103)	0.013 (0.103)	0.017 (0.104)				
<i>Constant</i>	-2.424*** (0.732)	-1.008 (0.778)	-1.093 (0.778)	-1.088 (0.778)	-0.579 (0.525)	-0.168 (0.574)	-0.212 (0.574)	-0.210 (0.574)	-0.535 (1.073)	-2.489 (1.566)	-3.500* (1.879)	-3.509* (1.885)
α_t	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
α_i	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES
<i>LDV</i>					0.664*** (0.027)	0.658*** (0.028)	0.657*** (0.028)	0.656*** (0.028)				
N	1194	1194	1194	1194	1194	1194	1194	1194	1194	1194	1194	1194
<i>R</i> ²	0.130	0.146	0.149	0.150	0.477	0.478	0.479	0.479	0.795	0.795	0.795	0.795
Adjusted <i>R</i> ²	0.116	0.132	0.134	0.135	0.468	0.469	0.470	0.470	0.644	0.644	0.643	0.643

Table 6 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 LN of the number of publications, weighted by journal quality and number of authors in the years 2008-2011.

Appendix C: Linear estimator

Estimating a linear model with Ordinary Least Squares (OLS) leads to predicted values which are negative or fractions of integers. Several studies using publication output as the dependent variable account for the limited domain of publication data (see e.g. Azoulay et al., 2010). Furthermore, the distribution of publication data is skewed with a spike at zero, which calls for a Tobit or a Heckman estimator. These estimators distinguish the extensive margin (is $y > 0$ or not) and the intensive margin (what is the value of y , given that $y > 0$). In the case of a Heckman estimator these two stages are both estimated explicitly, but knowing explicitly the external margin is not of high relevance here, because Handelsblatt only considers economists that actively undertake research. Thus, in principle the economists in our sample aim at publishing. Given that not every researcher achieves this goal in every year, using a Tobit estimator seems appealing. Because with non-linear panel fixed effect estimators the incidental parameter is transferred also to the explanatory variables, in practice a Poisson or a negative binomial estimator would be used following Santos Silva and Tenreyro (2006).

Nevertheless, with our sample we can apply a linear estimator for two reasons: First, with 79 cases, our sample of publication data displays exceptionally few zeros for bibliometric data. As shown in Appendix A these zero output observations have no pivotal influence on the results. Moreover, we do not just count the number of publications or the number of citations leading to count data. The support of the counts from the Handelsblatt ranking rather is the set of positive real numbers.