Susanne Breuninger, Kerstin Pull, Birgit Pferdmenges[*]

Like father(s), like son(s): Does the Relation between Advisor and Student Productivity Persist on Group Level?[**]

In light of the trend towards the Anglo-Saxon model of structured PhD education we analyze whether the positive relation between supervisor research productivity and young researcher productivity does persist in research *groups* where several PhD and postdoctoral students are supervised by a team of cooperating senior researchers. Our empirical analysis is based on a data set of 86 research training groups from different disciplinary fields funded by the German Research Foundation. We find that the positive relation between supervisor and student productivity also holds on group level. Controlling for group composition with respect to students' study background and demographics (age, gender and cultural background), we find evidence for age and gender diversity effects. Our results prove to be robust to a whole set of additional control variables such as group size, disciplinary field and advisor-student ratio.

Wie die Väter, so die Söhne: Der Zusammenhang zwischen Betreuer- und Nachwuchswissenschaftler-Produktivität auf Gruppenebene

Vor dem Hintergrund der zunehmenden Verbreitung strukturierter Doktorandenausbildung analysiert dieser Beitrag, ob der positive Zusammenhang zwischen der Produktivität von Betreuern und der Produktivität von Nachwuchswissenschaftlern auch in Forschergruppen besteht, in welchen mehrere (Post-)Doktoranden von einer Gruppe von Hochschullehrern betreut werden. Die empirische Analyse beruht auf einem Datensatz zu 86 DFG-geförderten Graduiertenkollegs aus unterschiedlichen Disziplinen. Es zeigt sich, dass der positive Zusammenhang zwischen der Produktivität von Betreuern und der Produktivität von Nachwuchswissenschaftlern auch auf Gruppenebene besteht. Dabei kontrollieren wir den Einfluss der demographischen und fachlichen Zusammensetzung der Nachwuchsgruppen und finden sowohl Alters- als auch Geschlechtseffekte. Unsere Ergebnisse sind robust gegenüber der Einbeziehung einer Reihe weiterer Kontrollvariablen wie etwa der Gruppengröße, der Disziplin oder dem Betreuungsverhältnis.

---

1.   Introduction

Among the many predictors of early career research productivity, advisor productivity has proven to be an important one (see e.g. Long & McGinnis, 1985; Williamson & Cable, 2003; Hilmer & Hilmer, 2007; Fiedler, Welpe, Lindlbauer, & Sattler, 2008). While from a theory perspective it is not clear whether we should expect the relation between student and advisor research productivity to be generally positive (it might well be that the very productive researchers find no time to adequately supervise their student researchers), the empirical findings in fact hint at a consistently positive relation between the two. This positive relation between student and advisor research productivity is likely to be the joint result of a set of diverse mechanisms: advisors passing on their *human capital* to their students, advisors introducing their students into the scientific community and hence endowing them with *social capital* and the more productive advisors being able to attract the more able and more productive doctoral and postdoctoral students (*self-selection/matching*). In our paper we do not aim at disentangling these potentially highly interrelated factors. Rather, we focus on whether a relation between advisor and student productivity is also to be found in the context of research *groups* and whether this relation is confounded or not by organizational group variables.

Our study on research *groups* is motivated by the fact that scientific research is increasingly characterized by collaboration (see Abramo, D'Angelo, & Di Costa, 2009) with the scientific environment steadily gaining importance for the process of knowledge production (see Stephan, 1996; Carayol & Matt, 2004). Specifically, concerning the supervision of young researchers, the last decades have witnessed a trend towards the Anglo-Saxon model of structured PhD education with doctoral students being supervised by more than one advisor and with the master-apprentice model as the traditional form of dissertation supervision in Germany (see Berning & Falk, 2004) successively losing ground. Among others, the German Research Foundation (*Deutsche Forschungsgemeinschaft – DFG*) has fostered this trend by constituting the so-called *Graduiertenkollegs* (Research Training Groups – RTGs) where a group of doctoral and postdoctoral students is supervised and supported by a group of cooperating researchers. Unlike it is the case in the traditional master-apprentice model, student members in an RTG are selected from a pool of applicants by a committee of participating researchers with supervisors and students not being matched right from the beginning, but rather in the process of the program (see e.g. Schneider & Sadowski, 2010). In light of the increasing importance of scientific collaboration in general and the relaxation of the one-to-one-relationship between supervisor and PhD student in particular, we ask whether the positive relation between supervisor research productivity on the one hand and young researcher productivity on the other does persist in research *groups* where several PhD and postdoctoral students are supervised by a team of cooperating senior researchers. If the relation between supervisor and young researcher productivity proves to hold and be persistent in the context of research groups, funding agencies should in fact favour applicants for RTG funding who display a high research productivity.

Further, we are interested in whether the relation between supervisor and young researcher productivity is confounded by group variables such as research group composition or group size. Controlling for group variables when analyzing the determinants of young researchers' productivity allows us to derive implications for the set-up of research training groups that go beyond selecting applicants with a high productivity.

The remainder of this paper is structured as follows: Section 2 reviews the literature and derives our base line hypothesis. Section 3 describes the data and methodology. Section 4 presents our findings. Section 5 comprises the results of our robustness checks within a discussion section and then summarizes our main results.

2. Theory: Linking supervisor and student research productivity

As to the determinants of research productivity, the literature identified a whole set of institutional and individual variables that are apt to influence research productivity. Among others, age (e.g. Goodwin & Sauer, 1995; Rauber & Ursprung, 2008), gender (e.g. Davis & Moore Patterson, 2001; Fabel, Hein, & Hofmeister, 2008), institutional reputation (e.g. Crane, 1965; Allison & Long, 1990; Long, Bowers, Barnett, & White, 1998), institutional size (e.g. Turner & Mairesse, 2005; Fabel, Hein, & Hofmeister, 2008), teaching load (e.g. Taylor, Fender, & Burke, 2006) and – last not least – supervisor research productivity (e.g. Long & McGinnis, 1985; Williamson & Cable, 2003; Hilmer & Hilmer, 2007; Fiedler et al., 2008) have shown to be important predictors of research productivity.

While from a theoretical perspective, the relation between advisor and student research productivity might be positive *or* negative (the latter resulting, e.g., from successful researchers being too busy to adequately supervise their students or from young researchers feeling discouraged by seemingly unachievably highly productive supervisors), the literature consistently points to the relation between advisor and student research productivity to be positive: E.g., Long and McGinnis (1985) find mentors to enhance students' pre-doctoral productivity via mentors acting as *teachers*, *networking sponsors* and *collaborators* – with the latter representing the single most important predictor of students' pre-doctoral research productivity. In a more recent study, Williamson & Cable (2003) investigate early career productivity of 152 management faculty accepting their first job and find that the research productivity of their dissertation advisors is directly positively related to their pre-appointment productivity and indirectly and positively related to their post-appointment productivity. Comparable to Long and McGinnis (1985), Williamson and Cable (2003) also regard the student-advisor relation as a formal mentoring relationship with advisors passing their knowledge and expertise to their doctoral students through "direct training, providing feedback on manuscript drafts, counseling on research agenda development, or helping protégés select appropriate research outlets for their work" (Williamson & Cable, 2003, p. 28). Based on the work by Williamson and Cable (2003), Fiedler et al. (2008) analyze the relation between the research productivity of postdoctoral students and their advisors and find advisor research productivity to be in fact the most important determinant of postdoctoral student productivity. While Hilmer and Hilmer (2007) also find student early research productivity to be positively related to that of his or her

dissertation advisor, theoretically they focus on the *self-selection* or *matching* process between doctoral students and dissertation advisors leaving room for a reversed causality when explaining the relationship between student and advisor research productivity with high ability doctoral students actively choosing the more productive dissertation advisors.

Summing up, the repeatedly and consistently found positive relationship between student and advisor research productivity is likely to be the joint result of a set of diverse mechanisms: (a) as teachers and collaborators advisors pass on their skills and expertise, i.e. their *human capital* to their students, (b) as networking sponsors advisors introduce their students into the scientific community hence endowing them with *social capital* and (c) the more productive advisors are able to attract the more able and more productive doctoral and postdoctoral students (*self-selection/matching*).

(a) human capital effect

There are several studies highlighting the positive relation between a researcher's *human capital* and his or her research productivity. In the majority of these studies, a researcher's human capital is not directly measured, but rather ascribed to the researcher by taking the reputation of the graduate program or the researcher's current and former affiliation as an indication of the amount of human capital he or she gathered (see e.g. Crane, 1965; Allison & Long, 1987; Rodgers & Maranto, 1989; Allison & Long, 1990; Maranto & Streuly, 1994; Long et al., 1998; Davis & Moore Patterson, 2001; Turner & Mairesse, 2005). Correspondingly, if the highly productive supervisors endow their students with more *human capital* than the less productive, young researchers' research productivity will be positively related to their supervisors' productivity. This should be true for a one-to-one-relationship between supervisor and young researcher, but it should also hold if a group of research students is supervised by a team of supervisors: I.e., the more highly skilled and experienced the team of supervisors in a research training group, the more human capital can be transferred to the doctoral and postdoctoral students (via direct counselling and/or via a more demanding and distinguished study program). While potential complementarities between the skills the different supervisors bring to the group might result in the human capital effect being even stronger on group than on individual level, one cannot exclude that it is less strong than on individual level, e.g. because supervisors of a research training group have lower incentives to invest in the skills of jointly supervised students than in those of individual advisees. To conclude, we expect the relationship between supervisor and student research productivity on group level to be positive, but the effect may be stronger or weaker as compared to the individual level.

(b) social capital effect

The central idea of most *social capital* approaches is that the social resources included in the networks provide benefits to the actors (see e.g. Coleman, 1988; Bourdieu, 1980; Boxman, de Graaf, & Flap, 1991). Also for researchers, the importance of networks has repeatedly been highlighted (see, e.g. Ismail & Rasdi, 2007), and a number of studies found that scientists who are cross-linked with their colleagues are more productive in publishing than others (see Allen, 1970; Blackburn, Behymer, & Hall, 1978;

Kyvik & Marheim Larsen, 1994). Summing up, if the highly productive supervisors endow their research students with more *social capital* than the less productive, young researchers' research productivity will likely increase with their supervisors' productivity. Again, this should be true for a one-to-one-relationship between supervisor and young researcher, but it should also hold if a group of research students is supervised by a team of supervisors – at least if the networks sponsored by the different supervisors do not conflict with one another, but rather productively add to or even complement each other. In case of conflicting networks, the relation between supervisor and student research productivity may be less pronounced on group level as it is on individual level, in case of complementary networks, it will be stronger.

(c) self-selection/matching effect

While the *self-selection/matching* process between research students and supervisors has not been studied in the literature as yet, one would in fact expect the more able and more productive research students to self-select into research groups led by the highly productive and well-reputed supervisors. Further, research students with a low productivity level might refrain from joining research groups comprised of highly productive supervisors – fearing that they will not be able to or have to work too hard to live up to the advisors' high expectations. Consequently, we expect young researchers' research productivity to be positively related to their supervisors' productivity. This will hold for research groups as well as for the traditional one-to-one relationship between supervisor and young researcher. Whether the self-selection/matching effect will be stronger or less strong on group level than on individual level, will – among others – depend on whether the supervisors in the research group are of similar or different research productivity: In case of a homogenous group of supervisors (with respect to their research productivity) self-selection/matching effects can be expected to be stronger than on individual level; in case of a heterogeneous group of supervisors, self-selection/matching effects will expectedly be weakened.

On the basis of the preceding analysis, we formulate the following hypothesis: *The relation between supervisor research productivity and young researcher research productivity in research groups is positive.*

3. Data, sources and variables

The empirical basis for our analysis is a data set of 86 Research Training Groups (RTGs) belonging to the humanities, social, natural and life sciences who were in their second funding period and who submitted their application for a third funding period to the German Research Foundation between October 2004 and October 2006. RTGs for doctoral and postdoctoral students were established by the German Research Foundation as an alternative to the traditional master-apprentice-model as a new form of doctoral education in the early 90s. Research Training Groups focus on a special research topic and are accompanied by a compulsory study program to provide students with the necessary methodological skills and specialized knowledge in the field of research. The RTGs are guided by a group of cooperating researchers who apply for the funding at the DFG, which lasts for a maximum of 9 years.

Dependent variable: RTG student publications

As journal articles have become undeniably the most important performance indicator, we chose as *dependent variable* for our analysis the mean journal article output of RTG students per funding year, i.e. per year and student scholarship for which the RTG received funding. The measure is equivalent to the number of journal articles of one RTG student in one year in which he was completely funded. In case of co-authorships, a share of 1/n is ascribed to all n authors of one journal article. We are not taking into account potential quality differences in publications and outlets as there does not exist a comparative journal ranking for the different disciplinary fields covered in our data (and even the disciplinary ones are often heavily discussed and by no means uncontroversial, see e.g. Kieser, 2012).

Obviously, journal articles are only part of total research output (comprising, among others, also monographs and articles in edited books) and hence do not represent a comprehensive measure of research output (see, e.g. Kieser, 2012, p. 97 for a similar assessment). While journal articles undoubtedly have gained importance (even in the humanities & social sciences), their significance still varies between the different disciplinary fields. Correspondingly, a low research output in an RTG in terms of very few journal publications is not equivalent to an overall low research performance. In light of the fact that the RTGs funded by the DFG aim at training "the next generation" of researchers one would expect young researchers to be introduced into the process of journal publications as these are gaining importance across all disciplines. However, in order to account for potential disciplinary differences, among others, we control for the disciplinary field within our robustness checks in section 5.1.

The publication data of the RTG students were hand-collected from the progress reports of the Research Training Groups that were part of the application for the third funding period. Hence, the Research Training Groups had a strong incentive to fully report their publication output in order to succeed with their application. Furthermore, Research Training Groups in the second funding period already existed long enough to be able to report publication output of their young researchers.

Explanatory variable: supervisor publications

Our central *explanatory variable* is the mean journal article output per supervisor and year. We chose a time span of five years (2001-2005) intending to grasp the "general research productivity" of the cooperating researchers. Again, in case of co-authorships, a share of 1/n is ascribed to all n authors of one journal article, and again we are not taking into account potential quality differences in publications and outlets.

The publication data of the advisors were collected from "Web of Science" *(Science Citation Index Expanded, Social Science Citation Index, Arts and Humanities Citation Index)*.

Control variables: Data on RTG composition

As we base our study on groups instead of individuals, we include *group characteristics* concerning the group of doctoral and postdoctoral students studying together in an RTG as further explanatory variables. Besides including the mean student age as an

indicator for the experience the RTG students on average dispose of, we further concentrate on diversity measures that have increasingly received attention in the literature on group performance (see, e.g. Simons, Pelled, & Smith, 1999 and Harrison & Klein, 2007 for group diversity effects in general and Hollingsworth, 2002; Porac, Wade, Fischer, Brown, Kanfer, & Bowker, 2004; Unger, Pull, & Backes-Gellner, forthcoming, for diversity effects in research groups). From a theoretical perspective, the relation between group diversity and group performance is not clear: On the one hand and highlighted by the so-called resource perspective (see, e.g. Hambrick & Mason, 1984; Gruenfeld, Mannix, Williams, & Neale, 1996), diversity might have positive effects on performance if team members possess distinct knowledge bases or abilities that are relevant for the production process. On the other hand, however, diversity might also negatively affect team performance because the communication between team members might be endangered, conflicts might arise and group cohesion might be reduced (so-called process perspective, see, e.g. Byrne, 1971; Tajfel, 1974; Turner, 1975). Arguably, the impact of diversity will depend on the type of diversity under consideration (with demographic types of diversity rather being net performance-reducing and functional background diversity rather being net-performance-enhancing; see e.g. Milliken & Martins, 1996; Williams & O'Reilly, 1998). In our study we distinguish between different types of diversity, i.e. diversity with respect to age, gender, cultural background and field of study. Following a repeatedly formulated claim in the diversity literature (see e.g. Jackson, Joshi, & Erhardt, 2003) we consider the multiple diversity dimensions simultaneously.

For the case of *age heterogeneity*, our only metric diversity variable, we use the variation coefficient of RTG student age as heterogeneity measure. The value of the variation coefficient is equal to 0 if all students are at the same age and rises with increasing heterogeneity.

To capture heterogeneity with respect to our categorical diversity variables *gender*, *cultural background* and *field of study*, we each employ the so-called Blau index (Blau, 1977) defined as

$$H = 1 - \sum_{i=1}^{n} s_i^2$$

with n representing the total number of categories of a variable, and s_i the fraction of team members falling into category i. Concerning fields of study in which the RTG students graduated we distinguish 22 different fields according to the "International Standard Classification of Education" (ISCED). Concerning students' cultural background we distinguish nine cultural regions according to the classification by Huntington (1996)[1] in his famous work on the "Clash of Civilizations". Afterwards, the Blau index is normalised on the interval [0,1] with the value of 1 representing maximal heterogeneity (see Alexander, Nuchols, Bloom, & Lee, 1995).

---

[1]   Unfortunately, we were not in a position to use the well-known classifications by Hofstede (1980), Trompenaars (1993) or GLOBE (House, Hanges, Ruiz-Quintanilla, Dorfman, Falkus, & Ashkanasy, 1999) because these did not cover all of the nations represented in our data set.

The data concerning cultural background, gender and age of the students come from a survey conducted by the German Research Foundation in 2005 where the RTGs were asked to report their students' characteristics. With our own complementary survey addressing the RTGs' spokespersons we further gathered information on students' fields of study.

4.   Results

Descriptives

Table 1 displays the means, standard deviations, minimum and maximum values of the variables used in our analysis. Regarding our dependent variable "mean journal article output of RTG students per funding year" we find that the most publication active RTG reports 0.81 journal articles of RTG students per funding year while the least active RTG reports 0 journal articles of RTG students per funding year; on average an output of 0.21 journal articles of RTG students per funding year is reported. While these numbers might seem quite low at first sight, it has to be remembered that we are considering very young researchers at the beginning of their academic career who encounter scientific research for the first time.

Concerning the central explanatory variable, the most active RTG with respect to the publication record of the cooperating researchers shows 2.17 journal articles per supervisor and year while the least active has 0 journal articles per supervisor and year.

Concerning group characteristics, we find the following: While the mean age of the RTG students is 29 years, the low mean variation coefficient concerning age (0.10) indicates that RTG students in one RTG tend to be of approximately the same age. Regarding gender heterogeneity, we find same-gender RTGs on the one hand (Blau-Index: 0) and mixed-gender RTGs with maximal heterogeneity (Blau-Index: 1, i.e. 50 percent males and 50 percent females) on the other hand. The mean gender heterogeneity is given by a Blau-Index of 0.80. With respect to cultural and field of study heterogeneity, there is a wide range in cultural diversity (Blau-Index: 0-0.75) and field of study composition (Blau-Index: 0-0.79).

Table 1*: Descriptives

	Min	Max	Mean	SD
Dependent variable				
mean journal article output of RTG students per funding year	0	0.81	0.21	0.14
Explanatory variable				
mean journal article output per supervisor and year	0	2.17	0.58	0.47
Control variables: Group characteristics				
mean age of RTG students	26.29	33.68	29.09	1.33
age heterogeneity of RTG students (variation coefficient)	0.05	0.16	0.10	0.02
gender heterogeneity of RTG students (Blau index)	0	1	0.80	0.22
cultural heterogeneity of RTG students (Blau index)	0	0.75	0.30	0.21
field of study heterogeneity of RTG students (Blau index)	0	0.79	0.35	0.27

Table 2 shows the correlations of the considered variables. Concerning our dependent variable, there are two statistically significant correlations: *First*, the relation between the mean age of the RTG students and the mean journal article output of RTG students per funding year is significantly positive ($r=0.29***$), suggesting that students' increasing experience leads to higher research productivity. *Second*, gender heterogeneity is negatively and statistically significantly related to the mean journal article output of RTG students per funding year ($r=-0.35***$), hinting at same-gender RTGs being more productive than mixed-gender RTGs. Concerning the correlation between our main explanatory variable "mean journal article output per supervisor and year", and our dependent variable "mean journal article output of RTG students per funding year", it is non-significant in the univariate analysis.

In order to test for potential multicollinearity, we examined the variance inflation factor. As all VIF values were below 1.6, there is no multicollinearity problem between these variables.

Table 2: Correlations

	1.	2.	3.	4.	5.	6.
1. mean journal article output of RTG students per funding year	-					
2. mean journal article output per supervisor and year	0.17	-				
3. mean age of RTG students	**0.29*****	**-0.20***	-			
4. age heterogeneity of RTG students	0.11	0.11	**0.38*****	-		
5. gender heterogeneity of RTG students	**-0.35*****	-0.15	-0.12	-0.02	-	
6. cultural heterogeneity of RTG students	-0.11	**0.30*****	-0.16	0.16	0.10	-
7. field of study heterogeneity of RTG students	-0.16	-0.12	0.07	0.04	**0.37*****	0.06

*** $p<0.01$; ** $p<0.05$; * $p<0.10$

OLS regression

Table 3 presents the results of our OLS regression with the dependent variable "mean journal article output of RTG students per funding year", the explanatory variable "mean journal article output per supervisor and year" and the group characteristics as further explanatory variables.

Consistent with our hypothesis, the mean journal article output per supervisor and year is positively and significantly related to the mean journal article output of RTG students per funding year. Hence, the positive relation between advisor productivity and student productivity also holds on group level. While the size of the effect is rather low and statistical significant only at the 10-percent-level, it must be kept in mind that in our analysis potential productivity differences between supervisors running a particular RTG are leveled out: I.e., an RTG with medium supervisor productivity might be rather homogeneous with its supervisors each displaying medium research productivity, but it might also be heterogeneous and consist of supervisors with either a very high or a very low research productivity. In the latter, heterogeneous, case, the high productivity supervisors might supply a disproportionately large

share of RTG students with human and/or social capital or attract a disproportionately large share of productive RTG students, leading to a higher research productivity on student level as compared to the one achieved in RTGs with homogeneous, medium supervisor productivity. In light of these potential leveling-out-effects in RTGs characterized by heterogenous supervisors, the measured effect would still seem sizable.

Beyond that, the mean age of the RTG students is positively related to the mean journal article output of RTG students per funding year, hinting at increasing experience in the early career leading to a higher research productivity. While we do not find significant effects regarding group heterogeneity with respect to age, cultural background and field of study, gender heterogeneity is significantly negatively related to the mean journal article output of RTG students per funding year. That means, same-gender RTGs are more productive with reference to journal publications than mixed-gender RTGs. When we take a closer look at the data, we find the negative relation between gender heterogeneity and (journal) publication output to only persist in the natural & life sciences and not in the humanities & social sciences (see Unger, 2010 for a comprehensive analysis of the RTG data with respect to diversity issues) – fitting well with the literature on co-education in maths and sciences on secondary school level (see e.g. Dick, 1992 and Horstkemper, 1992).

Table 3: OLS regression

explanatory variables	
mean journal article output per supervisor and year	0.0624*
mean age of the RTG students	0.0301**
age heterogeneity of RTG students	-0.0273
gender heterogeneity of RTG students	-0.1534**
cultural heterogeneity of RTG students	-0.0608
field of study heterogeneity of RTG students	-0.0320
R^2	0.2191
Adjusted R^2	0.1582
Prob > F	0.0034
N	84

*** $p<0.01$; ** $p<0.05$; * $p<0.10$

5.   Discussion and conclusion

5.1 Discussion

As a robustness check we employed a whole set of further control variables that might influence our dependent variable "mean journal article output of RTG students per funding year". However, due to the low number of cases, we were not in a position to include all potentially relevant variables in one estimation and therefore controlled for one after the other in separate regression analyses (see table 4).

As the size of a department or a graduate program has been shown to impact publication productivity (see, e.g. Dundar & Lewis, 1998; Buchmueller, Dominitz, &

Hansen, 1999; Carayol & Matt, 2004), we consider the size of an RTG measured as the sum of funding years as a first additional control variable. Further, we also control for the share of scholarship holders in relation to students being only associated to the RTG but not receiving funding with the latter group possibly experiencing further constraints concerning the time they can devote to publish their research. We further take into account the share of post-docs among RTG students – a measure potentially reflecting publication experience. As suggested in the literature (see, e.g. Bowen & Rudenstine, 1992) we also include the advisor-student-ratio measured as the number of students per supervisor potentially reflecting the intensity of supervision.

Table 4: OLS regressions – robustness checks

explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
mean journal article output per supervisor and year	0.0651*	0.0588*	0.0616*	0.0662*	0.0677	0.0709*	0.0627*	0.0885**
mean age of the RTG students	0.0302**	0.0306**	0.0244*	0.0308**	0.0274**	0.0272**	0.0302**	0.0247*
age heterogeneity of RTG students	-0.1104	-0.0407	-0.1253	-0.0799	-0.0250	0.0096	-0.0434	0.1811
gender heterogeneity of RTG students	-0.1530**	-0.1507**	-0.1437**	-0.1605**	-0.1526**	-0.1561**	-0.1580**	-0.1759**
cultural heterogeneity of RTG students	-0.0624	-0.0610	-0.0681	-0.0661	-0.1154	-0.1173	-0.0586	-0.0424
field of study heterogeneity of RTG students	-0.0334	-0.0288	-0.0267	-0.0394	-0.0223	-0.0256	-0.0352	-0.0224
RTG size	-0.0015							
share of scholarship holders		-0.0253						
share of post-docs			0.2769					
advisor-student ratio				-0.0122				
satisfaction with quality of supervision					0.0148			
existence of common workplaces/labs						-0.0016		
gender heterogeneity of supervisors							0.0123	
dummy humanities & social sciences								0.0516
R²	0.2227	0.2200	0.2346	0.2226	0.2097	0.2087	0.2196	0.2323
Adjusted R²	0.1511	0.1482	0.1641	0.1510	0.1306	0.1296	0.1478	0.1616
Prob > F	0.0061	0.0068	0.0038	0.0061	0.0171	0.0177	0.0069	0.0042
N	84	84	84	84	78	78	84	84

*** p<0.01; ** p<0.05; * p<0.10

Additionally, we take into account the satisfaction of the RTG students concerning the quality of supervision. Further, the existence of common workplaces or labs is

likely to facilitate the cooperation between the RTG students and might therefore influence the publication productivity of RTG students (see, e.g. Cummings & Kiesler, 2007). In light of the measured gender effect, we also gathered data on gender diversity on the level of RTG supervisors. Last not least, we controlled for the different disciplinary fields (humanities & social sciences on the one hand and natural & life sciences on the other).

The data on our additional control variables are taken from different sources: data on the disciplinary field was provided by the categorization of the German Research Foundation, data on RTG size, share of scholarship holders and postdocs, advisor-student-ratio as well as on the gender diversity of RTG supervisors were taken from the progress reports of the RTGs and data on the existence of common workplaces/labs as well as on the satisfaction of RTG students with the quality of supervision were taken from a complementary online survey we undertook addressing the RTG students themselves.

Except for the level of satisfaction with supervision, all additional control variables reveal no significant relations with the dependent variable "mean journal article output of RTG students per funding year" in the regression analyses, and their inclusion does not change our findings concerning the relationship between student research productivity on the one hand and advisor research productivity, mean student age and student gender diversity on the other. Interestingly, when we control for the level of satisfaction with supervision (column (5)), the relation between RTG student publication output and the output of their supervisors disappears – hinting at the more publication active supervisors being in fact perceived as the better supervisors. This interpretation is supported by the statistically significant positive correlation between supervisor output and the quality of supervision as perceived by the RTG students (r=0.30***).

5.2 Conclusion

Based on the finding that supervisor research productivity has shown to be an important predictor of research productivity (e.g. Long & McGinnis, 1985; Williamson & Cable, 2003; Hilmer & Hilmer, 2007; Fiedler et al., 2008) the aim of our study was to investigate if this relation also persists in research *groups*. Based on a dataset of 86 Research Training Groups funded by the German Research Foundation we showed that the individual positive relation between advisor productivity and student productivity is still in place when the individual relationships between student and advisor are loosened up - as it was intended by the establishment of the DFG-Research Training Groups.

While the size of the effect is comparatively low, our robustness checks hint at the relation between supervisor and student research productivity to be considerably robust with respect to introducing all different kinds of control variables: Students in a research training group are more productive in terms of journal publications when the advisors in the research training group also publish more in journals. Hence, if the German Research Foundation wants to encourage doctoral and postdoctoral students to increasingly publish their research in journals, it should take a look at RTG applicants' journal publication output. It goes without saying, however, that our study

clearly does not advocate that applicants' journal publication output should be the one and only criterion for a funding decision.

While we are the first to present evidence on the relation between advisor and student productivity on group level, our study also suffers from limitations: One first limitation concerns the fact that we only analyze correlations (though within a multi-variate analysis successively controlling for a wide range of variables) and are not in a position to detect causalities. In particular, we cannot distinguish empirically between human or social capital effects on the one hand where supervisors endow their students with skills and networks and seclection/matching effects on the other where students self select into research groups led by senior researchers that match their own research productivity level and/or ambitions. Further, our study is restricted with respect to the research productivity measure we use (journal publications). Clearly, journal publications only represent one (albeit increasingly important) part of a (young) researcher's research output, and further studies should strive at (a) broadening the perspective on research productivity by including other relevant output measures, (b) assessing potential quality differences between different articles (e.g., by citation analyses) and (c) further differentiating between different (sub-)disciplines and their potentially varying "production processes".

References

Abramo, G., D'Angelo, C. A., & Di Costa, F. (2009). Research collaboration and productivity: Is there correlation? *Higher Education, 57(2),* 155-171.

Alexander, J., Nuchols, B., Bloom, J., & Lee, S.-Y. D. (1995). Organizational demography and turnover: An examination of multiform and nonlinear heterogeneity. *Human Relations, 48(12),* 1455-1480.

Allen, T. J. (1970). Communication networks in R&D laboratories. *R&D Management, 1(1),* 14-21.

Allison, P. D., & Long, J. S. (1987). Interuniversity mobility of academic scientists. *American Sociological Review, 52(5),* 643-652.

Allison, P. D., & Long, J. S. (1990). Departmental effects on scientific productivity. *American Sociological Review, 55(4),* 469-478.

Berning, E., & Falk, S. (2004). Promotionsstudium - ein Beitrag zur Eliteförderung. *Beiträge zur Hochschulforschung, 26(3),* 54-76.

Blackburn, R. T., Behymer, C. E., & Hall, D. E. (1978). Research note: Correlates of faculty publications. *Sociology of Education, 51(2),* 132–141.

Blau, P. M. (1977). *Inequality and heterogeneity.* New York: Free Press.

Bourdieu, P. (1980). Le capital social. Notes provisoires. *Actes de la Recherche en Sciences Sociales, 31(1),* 2-3.

Bowen, W. G., & Rudenstine, N. L. (1992). *In pursuit of the Ph.D.* Princeton: Princeton University Press.

Boxman, E. A. W., de Graaf, P. M., & Flap, H. D. (1991). The impact of social and human capital on the income attainment of Dutch managers. *Social Networks, 13(1),* 51-73.

Buchmueller, T. C., Dominitz, J., & Hansen, W. L. (1999). Graduate training and the early career productivity of Ph.D. economists. *Economics of Education Review, 18(1),* 65-77.

Byrne, D. (1971). *The attraction paradigm.* New York: Academic Press.

Carayol, N., & Matt, M. (2004). Does research organization influence academic production? Laboratory level evidence from a large European university. *Research Policy, 33(8),* 1081-1102.

Coleman, J. S. (1988). Social capital in the creation of human capital. *The American Journal of Sociology, 94(special issue),* 95-120.

Crane, Diana (1965). Scientists at major and minor universities: A study of productivity and recognition. *American Sociological Review, 30(5),* 699-714.

Cummings, J., & Kiesler, S. (2007). Coordination costs and project outcomes in multi-university collaborations. *Research Policy, 36(10),* 1620-1634.

Davis, J. C., & Patterson, D. M. (2001). Determinants of variations in journal publication rates of economists. *The American Economist, 45(1),* 86-91.

Dick, A. (1992). Die Problematik der Koedukation im mathematisch-naturwissenschaftlichen Unterricht. In A. Grabosch, & A. Zwölfer (Eds.), *Frauen und Mathematik. Die allmähliche Rückeroberung der Normalität?* (S. 114-133). Tübingen: Attempto.

Dundar, H., & Lewis, D. L. (1998). Determinants of research productivity in higher education. *Research in Higher Education, 39(6),* 607-631.

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.

Fiedler, M., Welpe, I. M., Lindlbauer, K., & Sattler, K. (2008). Denn wer da hat, dem wird gegeben: Publikationsproduktivität des BWL-Hochschullehrernachwuchses und deren wissenschaftlicher Betreuer. *Zeitschrift für Betriebswirtschaft, 78(5),* 477-508.

Goodwin, T. H., & Sauer, R. D. (1995). Life cycle productivity in academic research: Evidence from cumulative publication histories of academic economists. *Southern Economic Journal, 61(3),* 728-743.

Gruenfeld, D. H., Mannix, E. A., Williams, K. Y., & Neale, M. A. (1996). Group composition and decision making: How member familiarity and information distribution affect process and performance. *Organizational Behavior and Human Decision Processes, 67(1),* 1-15.

Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. *Academy of Management Review, 9(2),* 193-206.

Harrison, D. A., & Klein, K. J. (2007). What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *Academy of Management Review, 32(4),* 1199-1228.

Hilmer, C. E., & Hilmer, M. J. (2007). On the relationship between the student-advisor match and early career research productivity for agricultural and resource economics Ph.D.s. *American Journal of Agricultural Economics, 89(1),* 162-175.

Hofstede, G. (1980). *Culture's consequences: International differences in work-related values.* Beverly Hills, CA: Sage.

Hollingsworth, J. R. (2002). Research organizations and major discoveries in twentieth-century science: A case study of excellence in biomedical research. Retrieved 01.06.2011, from http://skylla.wzb.eu/pdf/2002/p02-003.pdf

Horstkemper, M. (1992). Koedukation in mathematisch-naturwissenschaftlichen Fächern – zweifelhafter Gewinn für die Mädchen oder Entwicklungschance für alle? In A. Grabosch, & A. Zwölfer (Eds.), *Frauen und Mathematik. Die allmähliche Rückeroberung der Normalität?* (S. 114-133). Tübingen: Attempto.

House, Robert J., Hanges, P. J., Ruiz-Quintanilla, S. A., Dorfman, P. W., Falkus, S. A., & Ashkanasy, N. M. (1999). Cultural influences on leadership and organizations: Project GLOBE. In William H. Mobley, M. J. Gessner, & V. Arnold (Eds.), *Advances in global leadership.* (S. 171-233). Bingley, UK: Emerald Group Publishing Ltd.

Huntington, S. P. (1996). *The clash of civilizations and the remaking of world order.* New York: Simon & Schuster.

Ismail, M., & Rasdi, R. M. (2007). Impact of networking on career development: Experience of high-flying women academics in Malaysia. *Human Resource Development International, 10(2),* 153-168.

Jackson, S. E., Joshi, A., & Erhardt, N. L. (2003). Recent research on team and organizational diversity: SWOT analysis and implications. *Journal of Management, 29(6),* 801-830.

Kieser, A. (2012). JOURQUAL – der Gebrauch, nicht der Missbrauch, ist das Problem. *Die Betriebswirtschaft – Business Administration Review, 72(1),* 93-110.

Kyvik, S., & Marheim Larsen, I. (1994). International contact and research performance. *Scientometrics, 29(1),* 161–172.

Long, J. S., & McGinnis, R. (1985). The effects of the mentor on the academic career. *Scientometrics, 7(3-6),* 255-280.

Long, R. G., Bowers, W. P., Barnett, T., & White, M. C. (1998). Research productivity of graduates in management: Effects of academic origin and academic affiliation. *Academy of Management Journal, 41(6),* 704-714.

Maranto, C. L., & Streuly, C. A. (1994). The determinants of accounting professors' publishing productivity - the early career. *Contemporary Accounting Research, 10(2),* 387-407.

Milliken, F. J., & Martins, L. L. (1996). Searching for common threads: Understanding the multiple effects of diversity in organizational groups. *Academy of Management Review, 21(2),* 402-433.

Porac, J. F., Wade, J. B., Fischer, H. M., Brown, J., Kanfer, A., & Bowker, G. (2004). Human capital heterogeneity, collaborative relationships, and publication patterns in a multidisciplinary scientific alliance: A comparative case study of two scientific teams. *Research Policy, 33(4),* 661-678.

Rauber, M., & Ursprung, H. W. (2008). Life cycle and cohort productivity in economic research: The case of Germany. *German Economic Review, 9(4),* 431-456.

Rodgers, R. C., & Maranto, C. L. (1989). Causal models of publishing productivity in psychology. *Journal of Applied Psychology, 74(4),* 636-649.

Schneider, P., & Sadowski, D. (2010). The impact of new public management instruments on PhD education. *Higher Education, 59(5),* 543-565.

Simons, T., Pelled, L. H., & Smith, K. A. (1999). Making use of difference: Diversity, debate, and decision comprehensiveness in top management teams. *Academy of Management Journal, 42(6),* 662-673.

Stephan, P. E. (1996). The economics of science. *Journal of Economic Literature, 34(3),* 1199-1235.

Tajfel, H. (1974). Social identity and intergroup behaviour. *Social Science Information, 13(2),* 65-93.

Taylor, S. W., Fender, B. F., & Burke, K. G. (2006). Unraveling the academic productivity of economists: The opportunity costs of teaching and service. *Southern Economic Journal, 72(4),* 846-859.

Trompenaars, F. (1993). *Riding the Waves of Culture: Understanding Cultural Diversity in Business*. London: The Economist Books.

Turner, J. C. (1975). Social comparison and social identity: Some comparisons for intergroup behaviour. *European Journal of Social Psychology, 5(1),* 5-34.

Turner, L., & Mairesse, J. (2005). Individual productivity differences in public research: How important are non-individual determinants? An econometric study of French physicists' publications and citations (1986-1997). Retrieved 14.01.2011. from http://piketty.pse.ens.fr/fichiers/semina/ lunch/Turner2005.pdf

Unger, B. (2010). *Heterogenität und Performance von Forschernachwuchsgruppen. Eine Untersuchung am Beispiel von DFG-geförderten Graduiertenkollegs*. München, Mering: Rainer Hampp Verlag.

Unger, B., Pull, K., & Backes-Gellner, U. (forthcoming). Composition and performance of research training groups. In D. Jansen (Ed.), *The changing governance of higher education and research – comparative perspectives*. Dordrecht: Springer.

Williams, K. Y., & O'Reilly, C. A. (1998). Demography and diversity in organizations: A review of 40 years of research. *Research in Organizational Behavior, 20(20),* 77-140.

Williamson, I. O., & Cable, D. M. (2003). Predicting early career research productivity: The case of management faculty. *Journal of Organizational Behavior, 24(1),* 25-44.