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Is Scientific Performance a Function of Funds?

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The management of universities requires data on teaching and research performance. While teaching quality can be measured via student performance and teacher evaluation programs, the connection of research outputs and their antecedents is much harder to check, test and understand. To inform research governance and policy making at universities, the paper clarifies the relationship between grant money and research performance. We examine the interdependence structure between third-party expenses (TPE), publications, citations and academic age. To describe the relationship between these factors, we analyze individual level data from a sample of professorships from a leading research university and a Scopus database for the period 2001 to 2015. Using estimates from a PVARX model, impulse response functions and a forecast error variance decomposition, we show that an analysis at the university level is inappropriate and does not reflect the behavior of individual faculties. We explain the differences in the relationship structure between indicators for social sciences and humanities, life sciences and mathematical and natural sciences. For instance, for mathematics and some fields of social sciences and humanities, the influence of TPE on the number of publications is insignificant, whereas the influence of TPE on the number of citations is significant and positive. Corresponding results quantify the difference between the quality and quantity of research outputs, a better understanding of which is important to design incentive schemes and promotion programs. The paper also proposes a visualization of the cooperation between faculties and research interdisciplinarity via the co-authorship structure among publications. We discuss the implications for policy and decision making and make recommendations for the research management of universities.

Key words: research performance; decision making; third-party funds; publications; citations; PVARX model

JEL codes: M10 , C32 , C55.

Contents

1. Introduction

University research is essential for social knowledge creation. A reliable financing of universities contributes to continuous research activity. Since funds come generally from tax payers and/or students, universities face an ethical and moral obligation to allocate scarce resources efficiently. A decision making in the face of uncertainty, i.e. distribution of funds for research needs and purposes, urges research policy makers and university managers to understand the relationships between the dimensions of research performance and resulting or incoming grants.

Support of the effective decision making process requires qualitative together with quantitative information. It is important to properly reflect the interdependency between input and output variables of scientific knowledge production and also to account for time-delayed effects with appropriate methodology. This research contributes to a deeper understanding of the interplay between third-party funds (TPF), publications and citations. The resulting analysis reveals the significance of generally accepted beliefs in the scientific community and provides guidelines for improvement of decision making in university research management.

A lot of studies investigate the relationships between bibliometric indicators on an individual level (Abramo et al. 2013, Wildgaard 2016, Costas et al. 2010). However, an analysis of both bibliometric outputs and grant budget data mainly uses data at an aggregated level, i.e. institutes, faculties or departments (Bolli and Somogyi 2011, Dyckhoff et al. 2009). Few studies compare the bibliometric indicators with funds on the micro-level of research groups or university chair level (Jansen et al. 2007, Carayol and Matt 2004, Rosenbloom et al. 2015). Undertaking analysis on the level of individuals and subsequently merging outcomes into groups of interest could yield more robust and reliable results. Ebadi and Schiffauerova (2016) perform such statistical analysis of research funding of individual researchers listed in Natural Sciences and Engineering Research Council of Canada (NSERC) and their scientific outputs as recorded by Scopus. However, their study does not consider the financial support researchers receive from other funding institutions that may also affect the number of publications and citations. Mongeon et al. (2016) explore the distribution and marginal returns of research funding using data of the entire population of Québec academic researchers on funding, publications and average relative citations. Yet, they divide all researchers into three broad disciplines and perform analysis using the average and median of groups of 50 researchers. The discipline-specific characteristics are averaged within three research areas.

A distinctive feature of our study is the analysis of individual level data from a German university, which belongs to the top-10 universities is Germany in terms of external funds acquisition (DFG 2015). A sample of professorships, the complete set of their third-party expenses (TPE), publications, and citations from Scopus, is observed on a yearly basis for the period 2001 to 2015. Additionally, we include a variable academic age (number of years after PhD degree). This information enables the analysis on a fine level of granularity and provides the possibility to account for time-delayed effects.

Some researchers collaborate with their colleagues from other faculties and subsequently fields. As a result, their research outputs may reveal an interdisciplinary character that yields a heterogeneity. The analysis on individual data level allows to shed light on the heterogeneity of actual research outputs. To display the cooperation structure between faculties, we suggest to use a chord diagram (a technique commonly used in genetic engineering for genome data) and the information on co-authorship of publications. The sankey plot visualizes the resulting research interdisciplinarity.

Decision and policy making in research management must take into account the research fields' heterogeneity. Given thoughts about the feedback and interdependency, we employ a panel vector autoregressive model with exogenous variable (PVARX) (Canova and Ciccarelli 2013, Cavallari and D'Addona 2014). Aiming to underline the existing inter-faculty heterogeneity, we estimate the PVARX model for each faculty. The resulting impulse response functions (IRF) help to understand the relation between variables in a VAR context and clarify how a change in one variable affects another variable. For example, one may be wondering to what extent the number of publications will change, if the TPE increase by 1%. Since the analysis of such original innovations is rarely the case in work with real data (Tsay 2014), we proceed with orthogonalized innovations received using Choleski decomposition of the white noise covariance matrix. Finally, with the help of a forecast error variance decomposition (FEVD) we demonstrate a percentage of the variance of the prediction error explained by a shock at a four-year time horizon.

Our findings inform the university research management about the interrelationship between research performance indicators for each faculty and provide a range of possible explanations for the revealed patterns across scientific areas. We quantify the influence of TPE, publications and citations on each other, the reaction of the system to exogenous impulses and the amount of variance explained by considered variables. This perspective suggests the possibility to leverage the key resources according to the fields' needs and desired outputs. We summarize the results for social sciences and humanities, life sciences and mathematical and natural sciences. We also address the possible implications for policy and decision making and propose recommendations for university research management.

1.1. Related Literature

1.1.1. Third-Party Funds are financial input to the university or other institution from external sources on top of the regular university funds (Hornbostel 2001). An interesting variable is the amount of third-party funds (TPF) that was actually spent – third-party expenses (TPE) –, because the unused part of TPF generally must be returned to the funding agencies on a yearly basis.

The academic community debates the use of TPE for research performance evaluation. On the one hand, TPF is often accepted as an indicator of research performance, since competent experts from the corresponding subject fields carry out the peer review process before the allocation of TPF (German Council of Science and Humanities 2011). However, this applies not to all TPF. Apart from scientific funding organizations, universities receive a high amount of TPF from industry with a simplified selection process.

On the other hand, Sousa (2008) and Laudel (2005) caution against using TPE as an indicator of academic excellence. TPE measures only limited or not at all the quality of research or knowledge process. In contrast, bibliometric indicators and the results of the peer review process should be more appropriate for this purpose. Gerhards (2013) criticizes that in Germany the role of TPF is overemphasized in comparison to other countries. For instance, the assessment of the research quality in United Kingdom via the Research Excellence Framework (REF) and in the United States via the National Research Council (NRC) Ranking uses mainly publications and citations to measure the research performance of universities (REF 2011, NRC 2010). Gerhards (2013) points out that one should use TPF not as an output but as an input variable, which enables the research process and, as a result, publications, patents, inventions etc. He further concludes that TPF measures are not suitable as an indicator of research quality, unless the correlation between TPF and research results is strong enough. Therefore, it is important to determine and understand in which research areas high TPE can be associated with high research outputs and acknowledgement among scientific community.

Lariviere et al. (2010) emphasizes the various TPF demand in different research areas, in other words, the TPF varies a lot across research fields. For instance, natural and engineering sciences generally need expensive equipment that is often financed through TPF in order to start the research activity (Hornbostel 2001). At the same time, humanities and social sciences require mainly access to literature usually provided by the institution and research staff that could be financed though TPF. As concluded by Jansen et al. (2007), a significant difference emerges due to the field-specific practice of raising TPF. Thus, the absolute amount of TPE could only indicate the productivity in each field.

1.1.2. Publications and Citations generally act as an indicator of research productivity and resonance of research outlets. The majority of bibliometric studies focus on articles and literature reviews. One may exclude other document types because of the difficulties in comparison (Waltmann 2016).

In the same way as for TPE, the publishing and citing behavior differs across fields. For instance, social sciences and humanities have a tendency to publish in monographs, books or regional and national journals. Moreover, law sciences often publish in national language. Conference papers are the basic platform for introduction of research results for computer scientists, whereas in natural sciences and economics articles are standard. Because of the field specifics, publications in high-energy physics and biomedical sciences can count hundreds of authors and researchers in these areas correspondingly have significantly higher number of publications and citations. A more detailed overview of the publishing practice in various research areas is provided in Hornbostel and Torger (2015). Similarly, the citation behavior varies across fields. Hicks et al. (2015) and Bartol et al. (2014) introduce the significant difference in the number of citations in particular subject areas and point out the necessity to normalize.

Further, the language has direct influence on the number of citations of publication and as a result on international visibility of research (Gerhards 2013). The question whether to include non-English publications into the corpus is arguable. Although there are some studies that insist on including only English publications when comparing research institutions (van Leeuwen et al. 2001, van Raan et al. 2011), such approach will penalize the scientific fields with non-English publishing behavior.

An important factor influencing the outcome of analyses is the publication count. When analysing a publication that is written by, for example, two authors, one should decide which counting method to choose: full (assigning weight 1 to each author) or fractional (weight 0.5). This choice usually depends on the objective of a particular study. Moed (2005) explains the difference between full and fractional counting as the difference between participation and contribution. Waltmann (2015) provides a comprehensive literature review on the choice of counting method.

The time delay between the moment when the research work is published and starts to receive citations is called citation window (Glänzel and Schubert 2003). The size of the citation window influences the number of publications and citations that subsequent citation analysis will use. A large size of the citation window leads to the exclusion of more recent publications from the analysis, as they do not have enough time (equal to the length of the citation window) to collect the necessary citations (Waltmann 2015). On the contrary, when the citation window is too small, for instance one or two years, the mapping of the citations' impact can be incomplete. Setting the value of the citation window is important since it provides similar conditions for comparison of publications of different age. For instance, an article published ten years ago can collect much more citations than the one published five years ago ceteris paribus. Nevertheless, Abramo and D'Angelo (2011) study the differences between scientific areas and conclude that the long-term and short-term citation counts correlate strongly. In the case of a comparative analysis, the length of the citation window equal to three years can be used (Abramo et al. 2011). Therefore, the purpose of research should help with the choice of citation window: large window size for more accuracy or small size for stressing of timeliness (Wang 2013).

2. Research Model

The main TPF objective is support of research. It is natural to assume that the scientific outcome is presented to the scientific community through publication channels. Previous studies demonstrate that the research funding has positive impact on the knowledge production and publication output (Jacob and Lefgren 2011, Boyack and Borner 2003, Payne and Siow 2003, Rosenbloom et al. 2015, Bolli and Somogyi 2011, Carayol and Matt 2004). Using both bibliometric and regression analyses Ebadi and Schiffauerova (2015) and Ebadi and Schiffauerova (2016) confirm a strong relation between allocated funds and the productivity of researchers. According to the results of McAllister and Wagner (1981) this tendency is true for various fields of science. Furthermore, Beaudry and Allaoui (2012) identify a J-shaped curve explaining the significant positive effect of public funding on the publication rate. In other words, researchers with more funding produce even more publications. Summing up the literature, we propose the following hypothesis:

H1: Researchers with more funding have higher publication productivity, i.e. there is a positive impact of the past third-party funds on the current number of publications.

The allocation of TPF to researchers, as a result of a highly competitive peer-review process, is based inter alia on the prior research work. Beaudry and Allaoui (2012), Nag et al. (2013), Rosenbloom et al. (2015) show that past scientific productivity positively affects the likeliness of obtaining grants. A higher number of publications may result in a higher amount of acquired funding. Laudel (2005) explains a possible reason by the fact that researchers applying for external funds have to display some previous research papers. This suggests:

H2: The past productivity of researchers influences the likeliness of obtaining external funding, i.e. there is a positive effect of the number of publications in the past on the current amount of third-party funds.

Different from the strong positive influence on the quantity, allocated funds exhibit only partly a related effect on the quality of research outputs. Mongeon et al. (2016) report that the increase in funding leads to an increase in scientific impact, in other words citations – up to a certain level – are followed by a rapid decrease of marginal returns. They further explain that the reason may be different allocation of time, e.g. writing funding proposals or performing administrative tasks. The results obtained by Payne and Siow (2003) confirm a low and a negative relation between research funding and citations per article, thus, suggesting that the growth in expenditures yields in higher quantity but not necessarily quality of publications. This leads to:

H3: The academic funding of researchers influences the number of citations accumulated by their publications, i.e. there is a relationship between the amount of third-party funds and the number of citations.

Apart from indicators of scientific performance, the age of researchers may have a positive or negative influence on the other factors. As a result of analysis of researchers' data from different scientific fields, Cole (1979) shows that there is a minor curvilinear relation between age and indicators of research performance. He concludes that this influence is, however, low. Beaudry and Allaoui (2012) provide similar results. On the contrary, the analysis of Bonaccorsi and Daraio (2003) on the micro level demonstrates that the scientific productivity decreases with increasing age of scientists. Levin and Stephan (1991) provide evidence that on average there is a negative relation between age and productivity of researchers. Further, Abramo et al. (2016) show that this is true regardless the research area. Whereas Kyvik (1990) points out the differences in research fields for various age groups of scientists, indicating a greater decreasing trend in productivity for disciplines with frequent and extensive technical changes. Based on this review, we formulate two more hypotheses as:

H4: The scientific productivity of researchers changes with time, i.e. there is an effect of age on the number of publications.

H5: The amount of academic funding changes with the age of researchers, i.e there is an impact of age on third-party funds.

The research model with the corresponding hypotheses is illustrated in Figure 1.

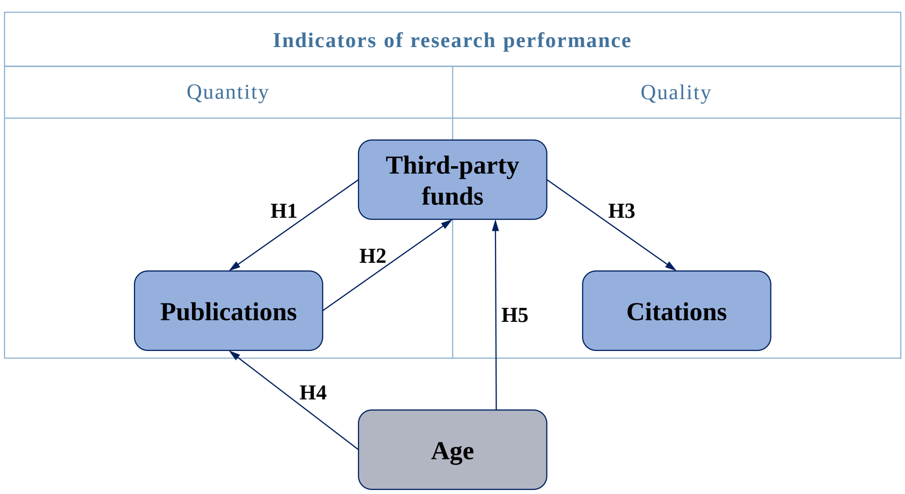

Figure 1 Summary of the research model and hypotheses

3. Data

We obtain the individual level data on TPE for professorships (scientific units of chair holders or lab owners) from a German university, which belongs to the top–10 German universities in terms of TPF acquisition (DFG 2015) and to the top–5 German universities according to a Times Higher Education's World University Ranking 2018 (THE 2018). The data covers the period 2001 to 2015. From an organizational point of view, each professorship belongs to one of eight faculties. However, three of the faculties (Faculty of Life Sciences, Faculty of Humanities and Social Sciences, Faculty of Mathematics and Natural Sciences) contain quite dissimilar institutes with regard to the differences in the corresponding research areas. For this reason, we split those faculties into the lower level and in the end receive 16 entities for analysis, see Table 1. For simplicity we further name these entities faculties and present descriptive statistics in the Supplemental file.

Original faculty		Analysed unit (faculty)	
Abbr.	Full name	Abbr.	Full name
Social sciences and Humanities			
Law	Faculty of Law	Law	
Phil1	Faculty of Arts and Humanities	Phil1	
Phil2	Faculty of Language, Literature and Humanities	Phil2	
Theo	Faculty of Theology	Theo	
Econ	Faculty of Economics and Business Administration	Econ	
CuSoEd	Faculty of Humanities and Social Sciences	Cult	Cultural History and Theory, Art and Visual History, Musicology and Media Studies, Archaeology, Asian and African Studies
		Soc	Social Sciences, Transdisciplinary Gender Studies
		Educ	Education Studies, Sports Sciences, Rehabilitation Sciences
Life sciences			
LifeSc	Faculty of Life Sciences	Agri	Agriculture and Horticulture
		Bio	Biology
		Psy	Psychology
Mathematical and Natural Sciences			
MNS	Faculty of Mathematics and Natural Sciences	Chem	Chemistry
		Geo	Geography
		Inf	Computer Science
		Mat	Mathematics
		Phys	Physics

Table 1 Organisational structure of analysed data

One should note that assistant professors, research assistants or other scientific members of the chair can gain their own third-party projects. Those TPE are also allocated to chair holders or lab owners, although the results of these research projects are not necessarily published under the chair's flag.

Furthermore, we match each chair holder who had TPE in the period 2001 to 2015 with his or her publications and citations listed in the Scopus database. We choose the Scopus database as a source for publications and citations, as it is currently the largest database of academic literature and it provides better coverage of publications and citations for the majority of disciplines compared to a Web of Science database by Thomson Reuters (Bergman 2012, Bartol et al. 2014, Waltmann 2015). The census date of the Scopus citation data is 31.08.2017. As a part of data preparation, we select publications of all document types for the selected corpus of authors, namely articles, conference papers, literature reviews, chapters, editorials, articles in press, erratums, notes, books, letters, short surveys and conference reviews. Hereby, we capture the outlets common for different subject fields. For the most faculties articles form the basis of the corpus. A well-known exception is computer science with a large part of conference proceedings, whereas law, social sciences and humanities outputs are found mostly in books, book chapters and conference proceedings. As a matter of fact, law, theology and social sciences have noticeably less recorded Scopus publications in comparison to other faculties.

As we are interested in the overall performance of faculties from the perspective of participation, we select the full counting method. We include all languages of indexed publications, in order to avoid penalization of scientific areas with non-English publishing behavior, for instance, social sciences and humanities. An overview of the proportion of languages of all publications from 2001 to 2015 is introduced in the Supplemental file. We also remove 8 outliers (3 from Biology, 5 from Physics) that have more than 100 co-authors within a single publication, as they are likely to distort the results. The development of the number of publications and citations per person over time for faculties is illustrated in the Supplemental file. More details on data preparation and descriptive analyses in various dimensions are provided in the Supplemental file.

A closer look into the database reveals that the average number of co-authors of publications differs among faculties. Therefore, when the cooperation structure through co-authorship is a point of interest, the research areas where less co-authors are common, e.g. social sciences and humanities, give less evidence for analysis. In contrast, the fields with several and more co-authors, e.g. natural and life sciences, provide a good basis for further investigations.

For illustration of internal (intramural) collaboration within university, we suggest to use a chord diagram in Figure 2 (left). One identifies joint publication channels among university members. The scale indicates the number of publications in the period 2001 to 2015. In the left panel we use grey lines to depict the collaboration across faculties. The corresponding connections are relatively thin. This indicates that the collaboration within faculties prevails, whereas the cross-faculty collaboration is less common. After excluding the publications within faculties, the research channels between faculties are more visible in Figure 2 (right). For instance, there are nearly 80 co-authorships between biological and agricultural faculties. More detailed analyses on intramural, national and international cooperation are referred to the Supplemental file.

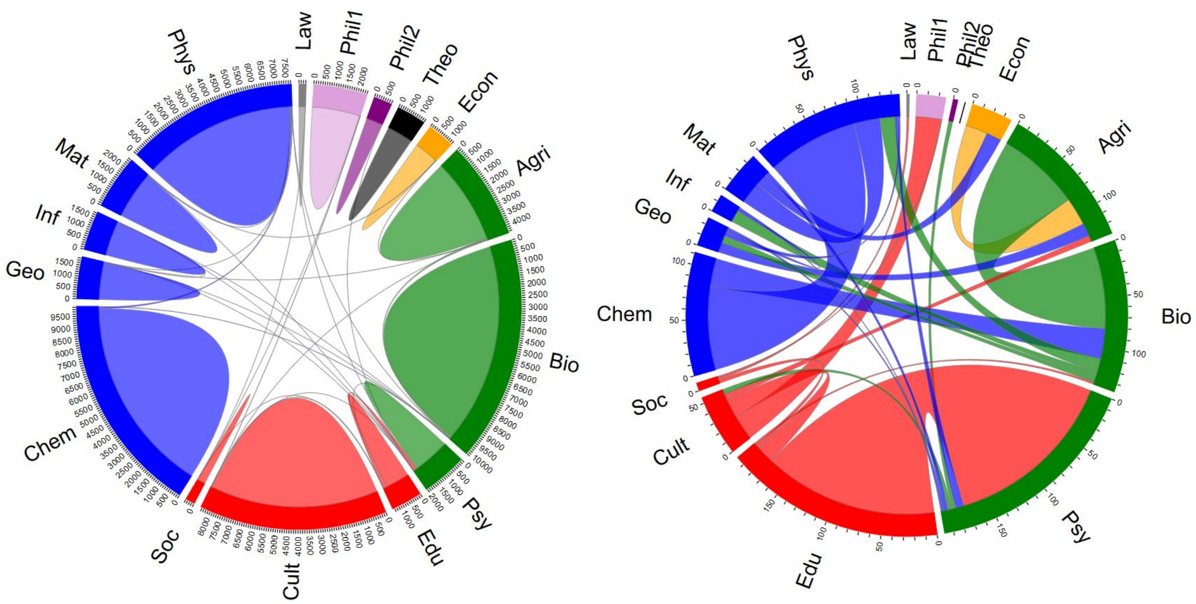

Figure 2 Chord diagram for the cooperation within entire university (left; 56579 coauthorships) and without internal cooperation inside faculties (right; 1122 co-authorships). Full counting, without 8 outliers. The color of the outer circle indicates the affiliation to the one of the 8 original faculties.

Since similar research fields can be assigned to different faculties, joint publications support the crossdisciplinary character of research. Insight into this cooperation pattern is illustrated on a sankey plot in Figure 3. The left part shows the 16 faculties, whereas the right part introduces 27 research fields taken from Scopus ASJC (All Science Journal Classification). The lines in between represent the number of publications written by specific faculty members in a certain research areas. Each publication is assigned to one of the subject areas according to the main direction of the journal or corresponding outlet where it was published. One conclusion from Figure 3 is that the majority of faculty publications is in its main profiling field. There is, however, a rich set of research outputs arising from other fields. Such an interdisciplinary pattern is evident for mathematical and natural sciences, life sciences, but also economics and educational sciences.

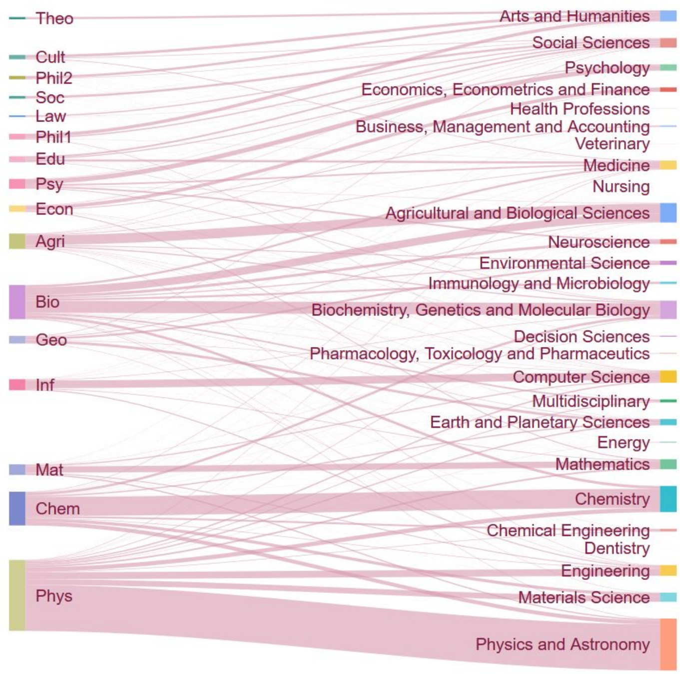

Figure 3 Sankey plot for publications published from 2001 to 2015 by professors of 8 faculties within 27 research fields. The width of the bars corresponds to the number of publications (totally 28034). Full counting, without 8 outliers.

In summary, the collaboration between faculties and correspondingly fields predetermines the interdisciplinary structure of research outputs. Not all faculty members cooperate to the same extent with their colleagues from other areas. Therefore, the various analyses between TPE, publications and citations that occur on individual data level may capture the heterogeneity and interdisciplinarity of the actual research results and not only the differences of the main field of researchers or their faculty.

4. Methodology

4.1. PVARX Model

The current state of TPE, publications and citations can be considered as a result of the historical development of each entity (the corresponding autocorrelation functions confirm this time series characteristic). This feature motivates the use of vector autoregressive (VAR) models, which are used in multivariate time series analysis. Since the information on the past is acknowledged additionally to the relationship structure between variables, VAR models allow to perform the data description, forecasting, structural and policy analysis in a clear and understandable manner (Stock and Watson 2001, Tsay 2014, Pfaff 2008).

The VAR(p) model of order p can be written as (Lütkepohl 2005, Koop and Korobilis 2010):

$$y_t = \alpha + \sum_{j=1}^{p} A_j y_{t-j} + \varepsilon_t,\ \ \varepsilon_t \sim N(0,\Sigma),\ \ (\varepsilon_t) \text{ i.i.d.} \tag{1}$$

where $y_t = (y_{1t}, \dots, y_{Kt})^\top$ is a $(K \times 1)$ vector of observations for $t = 1, \dots, T$, $\alpha = (\alpha_1, \dots, \alpha_K)^\top$ is a $(K \times 1)$ vector of intercepts, A_j is a $(K \times K)$ matrix of coefficients, $\varepsilon_t = (\varepsilon_{1t}, \dots, \varepsilon_{Kt})^\top$ is a $(K \times 1)$ vector of errors or innovations and p represents orders. Note that $\mathrm{E}(\varepsilon_t) = 0$, time invariant positive definite covariance matrix $\mathrm{E}(\varepsilon_t \varepsilon_t^\top) = \Sigma_\varepsilon$ and $\mathrm{E}(\varepsilon_t \varepsilon_q^\top) = 0$ for $q \neq t$.

The variables described in (1) are interdependent and endogenous. However, when the system has some variables that can affect others but are not influenced by them, it should be modeled rather through a VAR model with exogenous variables (VARX):

$$y_t = \alpha + \sum_{j=1}^{p} A_j y_{t-j} + \sum_{n=1}^{s} B_f x_{t-n} + \varepsilon_t, \tag{2}$$

where $x_t = (x_{1t}, \dots, x_{Mt})^\top$ is $(M \times 1)$ vector of exogenous variables, B_f is $(K \times M)$ matrix of coefficients, p is order for endogenous variables and s is order for exogenous variables.

Both models in (1) and (2) are used for time series observations of a single unit. However, empirical data often deal with multiple units. Such cross sectional dimension can be handled by panel VAR (PVAR) model (Canova and Ciccarelli 2013, Dees and Güntner 2014, Abrigo and Love 2016). For real data problems the PVAR model may appear to be restrictive. This can be avoided through including the exogenous variables into the model (Holtz-Eakin 1988, Juodis 2016, Fomby et al. 2013, Cavallari and D'Addona 2014, Djigbenou-Kre and Park 2016). Consequently, a PVARX(p, s) is given by:

$$y_{i,t} = \alpha_i + \sum_{j=1}^{p} A_j y_{i,t-j} + \sum_{n=1}^{s} B_f x_{i,t-n} + \varepsilon_{i,t}. \tag{3}$$

We estimate the VARX models using the R package MTS created by Tsay (2016). We also extend the package to support the multiple observations, i.e. to estimate the PVARX model. The corresponding R codes (Quantlets, see Borke and Härdle 2017 and Borke and Härdle 2018) are available at [Remove for blind review:] GitHub (`https://github.com/AlonaZharova/DMF`).

4.2. Model Specification

Since the hypotheses of interest and the theoretical assumptions regarding the interdependence involve causal relationship between the variables in both directions, we consider TPE, publications (PUB) and citations (CIT) as dependent variables and specify the model as a system of equations in (4). This design allows us to test our hypotheses.

$$\begin{aligned}
TPE_t &= \alpha_{10} + \sum_{i=1}^{p_1} \beta_{1i} TPE_{t-j} + \sum_{i=1}^{m_1} \gamma_{1i} PUB_{t-j} + \sum_{i=1}^{k_1} \delta_{1i} CIT_{t-j} + \zeta_{11} AGE_t + \varepsilon_{1t} \\
PUB_t &= \alpha_{20} + \sum_{i=1}^{m_2} \beta_{2i} TPE_{t-j} + \sum_{i=1}^{p_2} \gamma_{2i} PUB_{t-j} + \sum_{i=1}^{k_2} \delta_{2i} CIT_{t-j} + \zeta_{21} AGE_t + \varepsilon_{2t} \\
CIT_t &= \alpha_{30} + \sum_{i=1}^{m_3} \beta_{3i} TPE_{t-j} + \sum_{i=1}^{k_3} \gamma_{3i} PUB_{t-j} + \sum_{i=1}^{p_3} \delta_{3i} CIT_{t-j} + \zeta_{31} AGE_t + \varepsilon_{3t}
\end{aligned} \tag{4}$$

For instance, γ_{11} shows the linear dependence of TPE_t on PUB_{t-1} in the presence of TPE_{t-1}, CIT_{t-1} and academic AGE_t. The autoregressive structure of the data is emphasized via the lag operator, in other words time $t-j$. The academic age might influence other variables (Abramo et al. 2016 and Costas et al. 2010), but because of its nature cannot be affected itself. Therefore, the AGE is reflected in the model as an exogenous variable and is considered only in period t. The forecasting errors are encompassed by the corresponding ε.

In order to select the order p for the PVARX model, we calculate three information criteria: Akaike (AIC), Bayesian (BIC) and Hannan-Quinn (HQ). As a result of the analysis, all three information criteria choose order $p = 1$ according to their minimal values.

5. Empirical Results

5.1. Estimation

In order to understand the interdependence structure of faculties, we estimate the PVARX(1,0) model (4) for each faculty separately using least squares (LS) estimation. The results are summarized in Table 2, where we do not divide the CuSoEd (cultural, social and education sciences) faculty into three entities due to the lack of data on the lower aggregation level. The estimation results in the last sub-table introduce the average for the whole university.

Law

	TPE_t	PUB_t	CIT_t
$const$	1,804.74	0.13***	0.79
	(1,254.71)	(0.04)	(0.68)
TPE_{t-1}	0.87***	0.00	0.00
	(0.01)	(0.00)	(0.00)
PUB_{t-1}	1,399.97	0.28***	0.76
	(1,494.93)	(0.05)	(0.81)
CIT_{t-1}	168.23	0.01	0.03
	(153.80)	(0.00)	(0.08)
AGE_t	291.01***	0.00*	0.01
	(80.40)	(0.00)	(0.04)

Phil1

	TPE_t	PUB_t	CIT_t
$const$	5,972.56*	0.39***	1.82***
	(3,517.76)	(0.02)	(0.06)
TPE_{t-1}	0.91***	0.00***	0.00
	(0.03)	(0.00)	(0.00)
PUB_{t-1}	-607.89	0.49***	-0.12***
	(2,549.19)	(0.02)	(0.04)
CIT_{t-1}	57.10	0.01***	0.32***
	(392.73)	(0.00)	(0.01)
AGE_t	822.40**	-0.01***	-0.05***
	(360.01)	(0.00)	(0.01)

Phil2

	TPE_t	PUB_t	CIT_t
$const$	3,822.44***	0.23***	1.07***
	(1,165.35)	(0.02)	(0.02)
TPE_{t-1}	0.90***	0.00	0.00**
	(0.02)	(0.00)	(0.00)
PUB_{t-1}	279.35	0.35***	-0.02
	(1,421.20)	(0.03)	(0.03)
CIT_{t-1}	65.79	0.00	0.31***
	(141.61)	(0.00)	(0.00)
AGE_t	85.74	0.00	-0.04***
	(113.27)	(0.00)	(0.00)

Theo

	TPE_t	PUB_t	CIT_t
$const$	1,320.18	0.10**	0.12***
	(1,435.87)	(0.04)	(0.02)
TPE_{t-1}	0.97***	0.00	0.00*
	(0.03)	(0.00)	(0.00)
PUB_{t-1}	1,121.83	0.42***	0.01
	(1,537.81)	(0.04)	(0.03)
CIT_{t-1}	-218.40	-0.04	-0.06***
	(944.46)	(0.03)	(0.02)
AGE_t	113.67	0.02***	0.03***
	(119.68)	(0.00)	(0.00)

Econ

	TPE_t	PUB_t	CIT_t
$const$	-1,558.52	0.18***	4.53***
	(2,596.29)	(0.05)	(0.91)
TPE_{t-1}	0.93***	0.00***	0.00
	(0.02)	(0.00)	(0.00)
PUB_{t-1}	8,995.35***	0.53***	4.03***
	(1,826.19)	(0.03)	(0.64)
CIT_{t-1}	-212.44**	0.01***	0.28***
	(85.50)	(0.00)	(0.03)
AGE_t	163.77	0.02***	-0.10
	(248.88)	(0.00)	(0.09)

Agri

	TPE_t	PUB_t	CIT_t
$const$	6,361.74***	0.88***	22.60***
	(2,220.08)	(0.07)	(3.52)
TPE_{t-1}	0.98***	0.00***	0.00**
	(0.01)	(0.00)	(0.00)
PUB_{t-1}	1,169.96**	0.70***	0.94
	(491.50)	(0.02)	(0.78)
CIT_{t-1}	-22.72**	0.00***	0.64***
	(11.54)	(0.00)	(0.02)
AGE_t	-494.66**	-0.02**	-0.26
	(200.64)	(0.01)	(0.32)

Bio

	TPE_t	PUB_t	CIT_t
$const$	5,980.67***	1.51***	81.90***
	(1,303.04)	(0.06)	(2.28)
TPE_{t-1}	0.88***	0.00***	0.00
	(0.00)	(0.00)	(0.00)
PUB_{t-1}	2,729.29***	0.64***	4.71***
	(251.07)	(0.01)	(0.44)
CIT_{t-1}	-6.65	0.00***	0.38***
	(4.84)	(0.00)	(0.01)
AGE_t	-165.12	-0.01**	-2.14***
	(156.75)	(0.01)	(0.27)

Psy

	TPE_t	PUB_t	CIT_t
$const$	2,882.75	1.58***	66.04***
	(4,948.28)	(0.24)	(2.71)
TPE_{t-1}	0.79***	0.00***	0.00***
	(0.04)	(0.00)	(0.00)
PUB_{t-1}	1,807.83**	0.72***	-0.73
	(913.43)	(0.04)	(0.50)
CIT_{t-1}	24.75	0.00*	0.31***
	(27.64)	(0.00)	(0.02)
AGE_t	206.86	-0.04	-2.34***
	(498.13)	(0.02)	(0.27)

Chem

		PUB_t	CIT_t
$const$	5,212.58	1.87***	108.70***
	(6,135.88)	(0.15)	(11.39)
TPE_{t-1}	0.87***	0.00***	0.00*
	(0.02)	(0.00)	(0.00)
PUB_{t-1}	4,133.67***	0.74***	-0.68
	(743.76)	(0.02)	(1.38)
CIT_{t-1}	-13.71	0.00	0.48***
	(14.08)	(0.00)	(0.03)
AGE_t	-595.52**	0.03***	2.76***
	(300.71)	(0.01)	(0.56)

	Geo			**Inf**			**Mat**		
	TPE_t	PUB_t	CIT_t	TPE_t	PUB_t	CIT_t	TPE_t	PUB_t	CIT_t
$const$	579.18	0.85***	23.27***	-769.30	1.16***	11.89***	10,131.11***	0.69***	27.63***
	(3,215.81)	(0.04)	(0.59)	(3,431.72)	(0.12)	(2.06)	(2,570.37)	(0.13)	(3.93)
TPE_{t-1}	0.86***	0.00***	0.00***	0.92***	0.00**	0.00	0.98***	0.00	0.00***
	(0.04)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)
PUB_{t-1}	2,323.52**	0.67***	3.33***	3,243.46***	0.69***	3.69***	471.19	0.72***	-0.10
	(916.12)	(0.01)	(0.17)	(841.23)	(0.03)	(0.51)	(719.02)	(0.04)	(1.10)
CIT_{t-1}	8.54	0.00***	0.64***	-49.20	0.00**	0.30***	-4.73	0.00*	0.55***
	(14.84)	(0.00)	(0.00)	(56.68)	(0.00)	(0.03)	(12.22)	(0.00)	(0.02)
AGE_t	429.70	-0.05***	-0.83***	912.11***	-0.02***	-0.50***	-275.78	0.05***	0.00
	(346.87)	(0.00)	(0.06)	(251.73)	(0.01)	(0.15)	(308.02)	(0.02)	(0.47)

	Phys			**CuSoEd**			**University**		
	TPE_t	PUB_t	CIT_t	TPE_t	PUB_t	CIT_t	TPE_t	PUB_t	CIT_t
$const$	10,311.11**	1.60***	107.34***	5.42***	0.22***	1.34***	6,361.40***	0.13***	4.69***
	(5,063.36)	(0.15)	(4.78)	(1.53)	(0.02)	(0.20)	(551.12)	(0.01)	(0.55)
TPE_{t-1}	0.91***	0.00***	0.00	1.00***	0.00***	0.00	0.88***	0.00***	0.00**
	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PUB_{t-1}	1,349.77***	1.07***	14.36***	1.59	0.51***	2.84***	1,895.95***	0.96***	11.05***
	(373.63)	(0.01)	(0.35)	(1.43)	(0.02)	(0.19)	(181.41)	(0.00)	(0.18)
CIT_{t-1}	-17.16*	0.00***	0.31***	-0.06	0.01***	0.47***	-17.10***	0.00***	0.44***
	(8.83)	(0.00)	(0.01)	(0.07)	(0.00)	(0.01)	(4.58)	(0.00)	(0.00)
AGE_t	2,332.66*	-0.19***	-10.09***	-0.05	0.00	-0.07***	110.97*	0.00	-0.28***
	(1,205.19)	(0.03)	(1.14)	(0.18)	(0.00)	(0.02)	(58.28)	(0.00)	(0.06)

Table 2 Estimation results of PVARX(1,0) model. *, ** and * indicate a statistical significance at 1%, 5% and 10% level, respectively. Standard deviation is provided in brackets. Data: without 8 outliers, TPE are inflation adjusted with base year 2001, PUB with full counting.**

Table 2 introduces the relationships between all variables of interest. For instance, the estimated coefficients in the second column of the Biology institute (Bio) in sub-table (row 3, panel 1) illustrate how TPE responds to the change in TPE, PUB and CIT in the last period and in the current academic AGE after allowing for simultaneous change in other predictors in the provided data. If all other variables are held constant, then for each additional EUR in TPE in the previous year at the Bio faculty, one can expect the current TPE to increase by an average of 88 Cents. Further, TPE is predicted to increase by 2729 EUR given one additional publication in the preceding year. At the same time, CIT is insignificant for TPE. Likewise, after adjusting for simultaneous change in the other predictors, PUB responds with 0.64 publications to the one publication increment in the last year. Generally, TPE and CIT are highly significant for PUB, nonetheless their effect is miniscule. The intercepts suggest that one expects 5980 EUR, 1.5 publications and around 82 citations on average for Bio with no TPE, PUB and CIT influence. Interestingly, no statistically significant linear dependence of the mean of TPE on CIT and vice versa is found. The high p-value of the LS estimate of AGE indicates that the academic age is not statistically significant even at the 10% level for TPE. However, a one year increase of academic AGE decreases the predicted PUB level by 0.01 publications and CIT level by 2.14 citations.

We are now prepared to check the hypotheses *H1 – H5*. As can be seen from Table 3, *H1* (TPE drives publications) is rejected for Law, Phil2, Theo and Mat, as the variable TPE_{t-1} is not significant for the variable PUB_t at the $\alpha = 10\%$ significance level. In the same manner, we check the remaining *H2 – H5* for all faculties and the whole university, see Table 3.

Hypotheses	Law	Phil1	Phil2	Theo	Econ	Agri	Bio	Psy	Chem	Geo	Inf	Mat	Phys	CuSoEd	Uni.
H1		+			+	+	+	+	+	+	+		+	+	+
H2					+	+	+	+	+	+	+		+		+
H3			+	+		+		+	+	+		+			+
H4	+	−		+	+	−	−		+	−	−	+	−		
H5	+	+				−			−		+		+		+

Table 3 **Hypotheses that are rejected (gray) or failed to reject (blue) for each faculty according to the 10% significance level of corresponding variables. The sign denotes the positive (+) or negative (−) influence.**

The analysis reveals interesting patterns. First, the social sciences, humanities and mathematics generally have insignificant relationship between PUB and TPE. Second, the detected influence of TPE on CIT is positive and, interestingly, is present even for fields with no relationship between TPE and PUB. This seems to indicate a difference between quality and quantity of research outputs. Third, the AGE of researchers from the same faculty influences PUB and TPE differently, in the sense of the significance level and sign of the effect. Furthermore, one can clearly see that the results for the whole university in the last column considerably differ from the results of the faculties. This demonstrates that analyses on the high aggregation level of the university do not reflect the behavior of its faculties.

5.2. Structural Analysis

5.2.1. Impulse Response Functions VAR models also provide the possibility to track the reaction of the system given an exogenous impulse. The corresponding impulse response functions (IRF) describe the relations between variables of the system. Orthogonalized IRF allow to change one variable to the value of its standard deviation shock and to track how the other variable consequently changes over time. The condition is that all other variables have no shocks. Technical details of the methodology can be found in Lütkepohl (1999) and Baltagi (2001). Thus, the IRF shows us how TPE, PUB and CIT change during coming periods, if they are influenced by a specific impulse.

Figure 4 shows the dynamic interrelationships within the system from the fitted PVARX(1,0) model with orthogonalized innovations. The first row shows an effect of one standard deviation shock in TPE (panel 1,1), PUB (1,2) and CIT (1,3) on TPE, given there are no other shocks in the system. The second and the third rows introduce the responses in PUB and CIT correspondingly to a specific unit innovation.

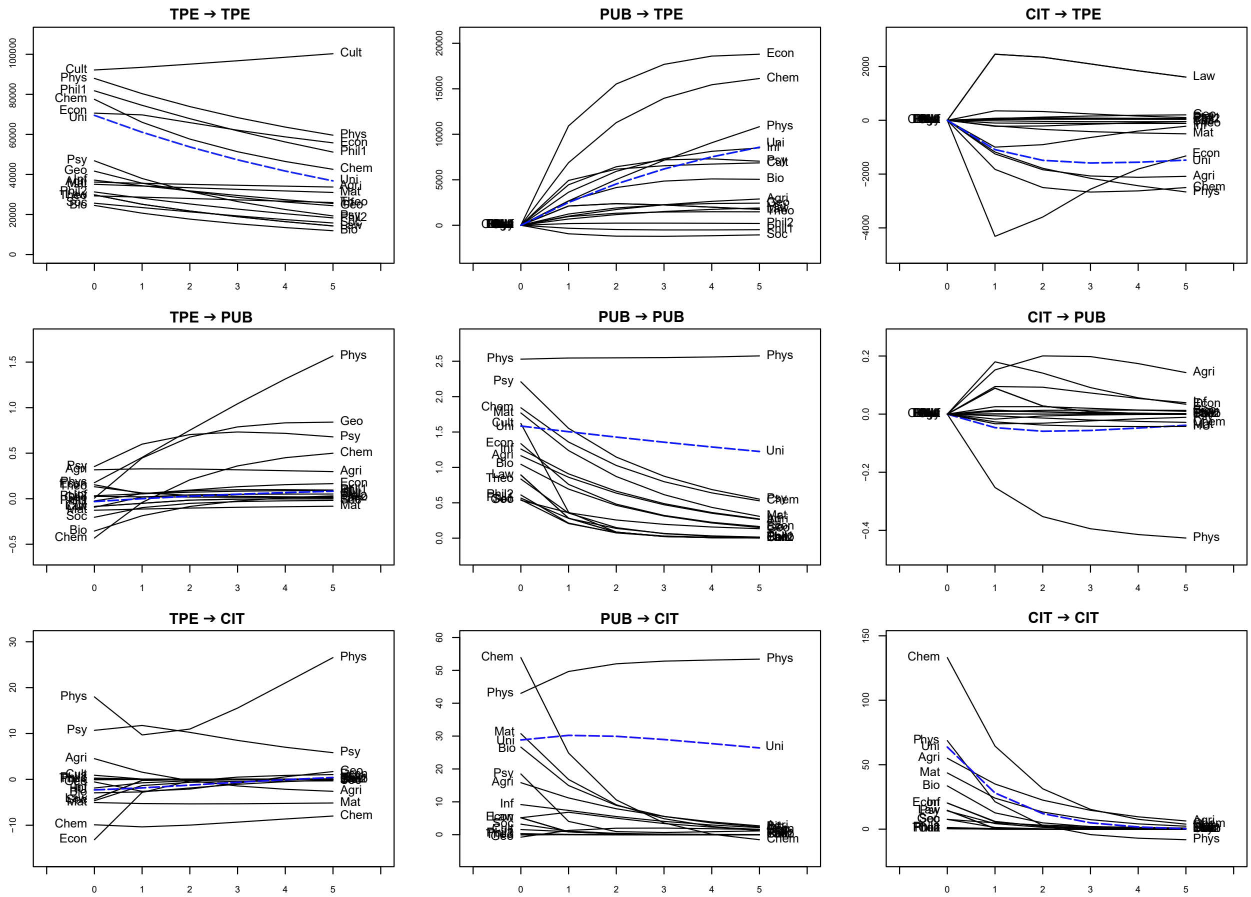

Figure 4 Impulse Response Functions of the PVARX(1,0) model for TPE, CIT und PUB for faculties (black lines) and university (blue dashed line) for the first 5 periods. Innovations are orthogonalized (impulse → response).

The ordering of variables is important for the definition and interpretation of the IRF. We select the order according to the estimation results and implies that TPE is a variable with potential immediate effect on itself and other variables, the shock in PUB can have instantaneous impact on the last two variables and CIT may influence only the last component of the row. For instance, the first row indicates that TPE may affect all three variables, PUB may influence TPE and CIT, while CIT has potential effect on TPE with some time lag.

The results show that by increasing TPE of Econ in period t_0 by one standard deviation one can expect a 70000 EUR increase in TPE in the first year t_1, see plot (1,1) in Figure 4. In periods t_2 to t_5 from 68000 EUR to 60000 EUR of TPE are additionally obtained by Econ on a yearly basis. In other words, Econ may gain approximately 330000 EUR cumulatively at the end of the fifth year given one standard deviation innovation increase in TPE in the starting period t_0.

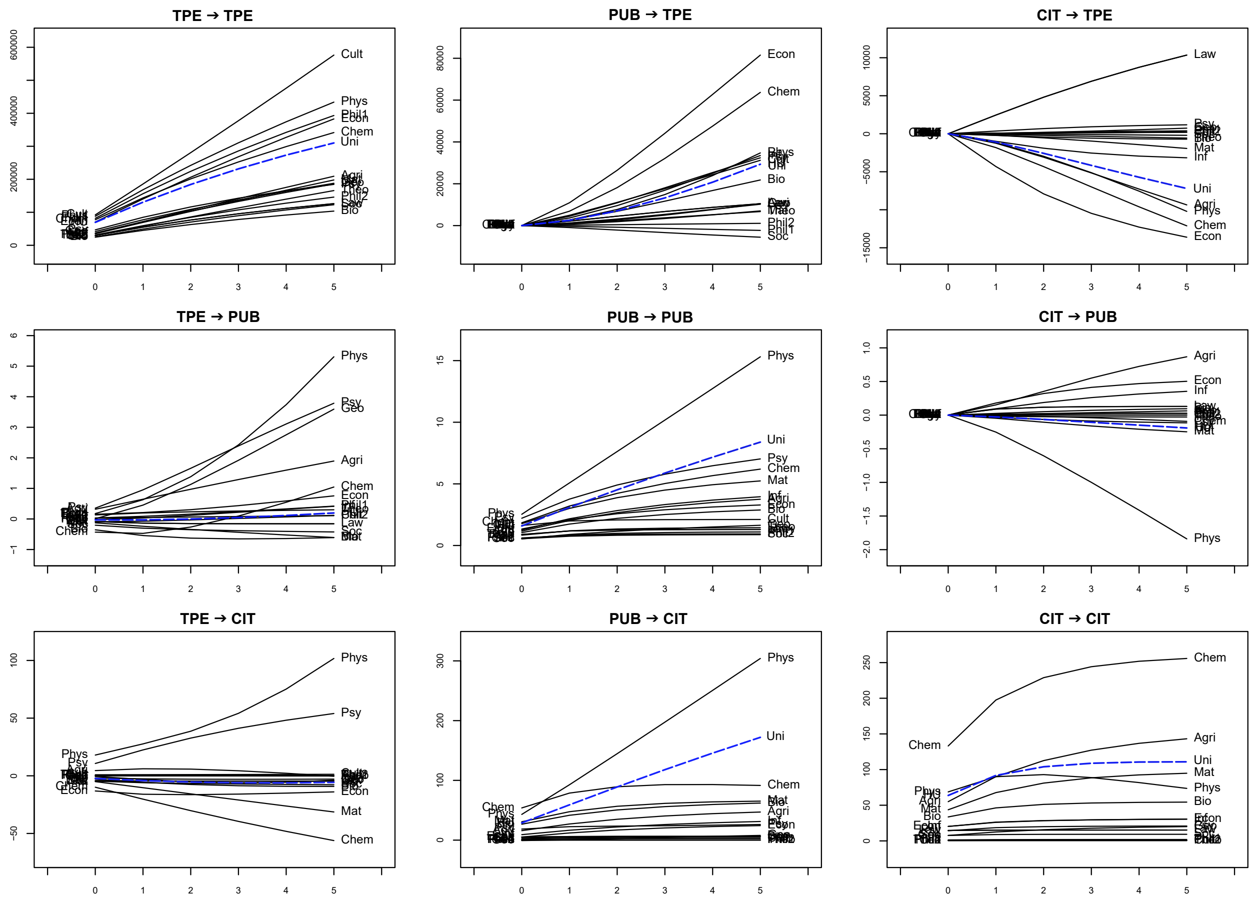

Figure 5 Cumulated IRF of the PVARX(1,0) model for TPE, CIT und PUB for faculties (black lines) and university (blue dashed line) for the first 5 periods. Innovations are orthogonalized (impulse → response).

In a similar manner, the plot (1,2) shows that the TPE response with a time lag of one period and a value of around 7000 EUR on an innovation in PUB for Chem. By t_5 the TPE reaches nearly 17000 EUR per year or nearly 62000 EUR in total for five periods for Chem. Next, one standard deviation shock in CIT in Econ leads to 400 EUR decrease by the first year and then demonstrates a further gradual decline, as it still stays below zero, see (1,3). A shock in TPE has also an immediate impact on PUB. The plot (2,1) depicts a slow but steady increase of PUB from t_0 to t_5 for almost all faculties, when it is influenced by a one standard deviation shock in TPE. A positive but over time declining impact has a shock in PUB on itself for all faculties, except Phys, which is slowly increasing with each additional year, see (2,2). However, an innovation in CIT (2,3) does not lead to considerable changes in PUB in the long term perspective, again with exception of Phys. The plot (3,1) shows that CIT remain more or less stable for all faculties, but Phys, influenced by a shock in TPE. For CIT a positive effect of PUB (3,2) and CIT (3,3) innovations rapidly dies away during t_1–t_3. Only Phys demonstrates an opposite trend. The response in all variables to a shock in itself is positive, gradually decreasing for TPE over time (Cult being an exception) and more sharply for PUB (Phys being an exception) and CIT in the first three years. The long-term effects or accumulated responses with orthogonal innovations over five periods to a unit shock are introduced in Figure 5.

One can clearly see that the impulses in the same variables cause different responses within faculties. However, the IRF of the university introduces an aggregate that diminishes field-specific behavior. For instance, the cumulated IRF for PUB→PUB, CIT→PUB and PUB→CIT show that the Uni-level increase seems to be heavily driven by a single faculty Phys.

To summarize, we see the possible evolution of TPE, PUB and CIT for all faculties and university along a five years time horizon after a shock in t_0 via IRF. Moreover, the IRF results further support the view that university level decisions, which may affect all heterogeneous faculties, should not be based on university level data.

The issue with IRF is that if some important variables are not included into the system, their effect is captured by innovations and consequently can result in some bias in IRF. The FEVD overcomes this issue as it shows to what extent the change in variables is explained by external shocks.

5.2.2. Forecast Error Variance Decomposition (FEVD) helps to measure the forecast' preciseness of a fitted VAR model (Tsay 2014). It shows which part of the forecast error variance is explained by a shock at a given horizon h. In other words, one expects to see how many percent of the change in the forecast errors of TPE, PUB and CIT relates to the exogenous shocks of these variable. FEVD denotes a percentage of the variance of the forecast error explained by a shock at a given horizon h. Table 4 shows the FEVD results from 1- to 4-step ahead predictions.

		Law			**Phil1**			**Phil2**			**Theo**			**Econ**		
F. error	h	Variance decomposition			Variance decomposition			Variance decomposition			Variance decomposition			Variance decomposition		
		TPE	*PUB*	*CIT*	*TPE*	*PUB*	*CIT*	*TPE*	*PUB*	*CIT*	*TPE*	*PUB*	*CIT*	*TPE*	*PUB*	*CIT*
TPE	1	100.00	0.00	0.00	100.00	0.00	0.00	100.00	0.00	0.00	100.00	0.00	0.00	100.00	0.00	0.00
	2	99.31	0.29	0.39	99.99	0.00	0.00	99.99	0.00	0.00	99.95	0.05	0.00	98.62	1.19	0.19
	3	98.92	0.50	0.57	99.99	0.00	0.00	99.99	0.00	0.00	99.89	0.11	0.00	97.31	2.47	0.22
	4	98.69	0.64	0.67	99.99	0.00	0.00	99.99	0.00	0.00	99.85	0.15	0.00	96.21	3.59	0.20
PUB	1	0.91	99.09	0.00	0.18	99.82	0.00	0.18	99.82	0.00	2.44	97.56	0.00	1.30	98.70	0.00
	2	1.10	98.01	0.89	0.90	99.08	0.03	0.26	99.74	0.00	2.54	97.42	0.03	1.10	97.56	1.34
	3	1.11	97.92	0.97	2.67	97.29	0.04	0.34	99.66	0.00	2.64	97.32	0.04	1.33	96.72	1.95
	4	1.12	97.91	0.98	4.81	95.15	0.04	0.39	99.61	0.00	2.71	97.26	0.04	1.88	95.96	2.16
CIT	1	7.12	10.26	82.62	0.36	4.30	95.34	16.95	20.37	62.68	1.62	2.71	95.67	28.27	4.34	67.39
	2	7.11	10.50	82.39	0.35	3.94	95.70	16.31	20.19	63.50	1.85	2.81	95.34	25.91	10.47	63.62
	3	7.11	10.52	82.37	0.36	3.93	95.71	16.22	20.15	63.63	2.01	2.81	95.18	24.84	13.48	61.69
	4	7.11	10.52	82.36	0.37	3.96	95.67	16.33	20.11	63.56	2.17	2.81	95.02	24.43	14.79	60.79

		Agri			**Bio**			**Psy**			**Chem**			**Geo**		
F. error	h	Variance decomposition			Variance decomposition			Variance decomposition			Variance decomposition			Variance decomposition		
		TPE	*PUB*	*CIT*	*TPE*	*PUB*	*CIT*	*TPE*	*PUB*	*CIT*	*TPE*	*PUB*	*CIT*	*TPE*	*PUB*	*CIT*
TPE	1	100.00	0.00	0.00	100.00	0.00	0.00	100.00	0.00	0.00	100.00	0.00	0.00	100.00	0.00	0.00
	2	99.90	0.04	0.06	99.31	0.69	0.00	99.45	0.54	0.00	99.51	0.45	0.03	99.95	0.05	0.00
	3	99.77	0.11	0.13	98.21	1.78	0.01	98.69	1.31	0.00	98.67	1.26	0.07	99.87	0.13	0.00
	4	99.63	0.18	0.18	97.05	2.95	0.01	97.92	2.08	0.01	97.69	2.21	0.10	99.79	0.21	0.00
PUB	1	6.91	93.09	0.00	10.37	89.63	0.00	2.49	97.51	0.00	5.20	94.80	0.00	0.02	99.98	0.00
	2	8.95	90.06	0.99	9.29	90.67	0.04	6.22	93.76	0.01	3.46	96.54	0.00	32.44	67.55	0.01
	3	10.92	86.88	2.20	8.61	91.33	0.07	10.23	89.75	0.02	3.53	96.46	0.00	57.71	42.26	0.02
	4	12.81	84.03	3.16	8.22	91.70	0.08	13.93	86.04	0.02	4.94	95.05	0.01	71.08	28.89	0.03
CIT	1	0.62	7.60	91.78	0.46	38.40	61.13	17.36	51.91	30.73	0.47	14.02	85.51	0.54	0.97	98.50
	2	0.49	8.07	91.44	0.72	41.68	57.60	30.36	43.05	26.59	0.80	13.76	85.44	7.75	2.47	89.78
	3	0.44	8.38	91.18	0.83	43.17	56.00	38.05	38.20	23.75	1.14	13.57	85.30	10.54	5.56	83.90
	4	0.46	8.57	90.98	0.87	43.81	55.32	42.45	35.49	22.06	1.44	13.44	85.11	10.31	8.53	81.16

		Inf			Mat			Phys			CuSoEd			University		
F. error	h	Variance decomposition			Variance decomposition			Variance decomposition			Variance decomposition			Variance decomposition		
		TPE	PUB	CIT	TPE	PUB	CIT	TPE	PUB	CIT	TPE	PUB	CIT	TPE	PUB	CIT
TPE	1	100.00	0.00	0.00	100.00	0.00	0.00	100.00	0.00	0.00	100.00	0.00	0.00	100.00	0.00	0.00
	2	99.45	0.51	0.04	99.98	0.02	0.00	99.94	0.05	0.01	99.98	0.01	0.00	99.91	0.07	0.01
	3	99.45	0.51	0.04	99.94	0.05	0.00	99.81	0.16	0.02	99.97	0.02	0.00	99.74	0.23	0.03
	4	97.71	2.24	0.05	99.90	0.09	0.01	99.62	0.34	0.04	99.96	0.03	0.01	99.48	0.47	0.04
PUB	1	0.07	99.93	0.00	0.51	99.49	0.00	0.48	99.52	0.00	0.00	1.00	0.00	0.04	99.96	0.00
	2	0.16	99.46	0.37	0.61	99.34	0.05	1.80	97.72	0.48	0.18	98.56	1.26	0.02	99.96	0.01
	3	0.32	99.07	0.61	0.72	99.18	0.10	3.94	95.13	0.92	0.58	97.18	2.25	0.03	99.94	0.03
	4	0.51	98.76	0.73	0.82	99.03	0.15	6.72	92.06	1.22	1.16	96.08	2.77	0.05	99.91	0.04
CIT	1	0.71	16.84	82.45	0.89	32.88	66.23	4.69	6.84	68.47	1.16	1.83	97.02	0.11	16.97	82.93
	2	0.70	23.45	75.85	1.41	32.60	65.98	4.21	43.57	52.22	1.20	7.69	91.11	0.13	26.41	73.45
	3	0.67	27.01	72.32	2.02	32.33	65.66	4.22	55.11	40.68	1.18	11.41	87.41	0.13	34.53	65.34
	4	0.66	28.82	70.52	2.64	32.07	65.29	4.93	62.13	32.93	1.15	13.28	85.57	0.13	40.88	59.00

Table 4 Forecast error variance decomposition of the TPE/PUB/CIT system with the forecast horizon h. The color intensity indicates the degree of explained variance (light blue for 1.00%–25.00%, blue for 25.01%–75.00% and darker blue for 75.01%–100%)

The results demonstrate low interrelation between TPE and other time series. For instance, from 96% to 99% of 2- to 4-steps forecast error variance of TPE is accounted for by shocks in TPE. As with the IRF, this can be partly explained by the selected order of variables. Similarly, from 95% to 99% of the error in PUB can be attributed to the innovations in PUB for social sciences, humanities and informatics. For life sciences and geography, the changes in TPE partly explain the variation in PUB. Moving from 1- to 4-steps forecast horizon, the development in the forecast error variance of CIT that can be explained by its own innovations decreases, whereas the contribution of the PUB and in some cases TPE shocks increases. Such slowly growing influence of other variables is also true for TPE and PUB. The variance in CIT for law, natural and life sciences and language sciences is largely explained by variation in PUB and to a smaller extent in TPE. Interestingly, for economics and management sciences the variation in CIT is better explained by errors in TPE than in PUB. Moreover, the error variance in CIT for psychology is accounted for by PUB and TPE innovations to a greater extent than by CIT itself.

Summarizing the FEVD insights, we identify for which faculties TPE, PUB and CIT act as driving forces of the change of the forecast error of corresponding predictions. We find that the variance of the TPE is mainly related to shocks in TPE. A variance change in PUB and CIT partly corresponds to the shocks in all three systems' variables for most of the faculties. One can also conclude that there are some omitted variables that possibly influence the system. This is especially true for TPE, as innovations in PUB and CIT explain its forecast error variance to a low degree or not at all for different faculties. The FEVD results also confirm the view that the results for the university do not reflect the features of single faculties. More importantly, one can see the difference in the explained variance for various faculties and correspondingly research fields.

6. Summary and Discussion

The paper contributes to the discussion on interdependence structures between third-party expenses (TPE), publications (PUB) and citations (CIT). Contrary to most previous studies, we use individual data that provides insight at the highest granularity level and leads to more robust results when aggregating to the faculty level.

Analyzing the data we employ a sophisticated state-of-the-art methodology which has never been used before in the context of research performance. Our work extends the previous research by using a VAR type model that is usually employed in macroeconomic analyses (Holtz-Eakin 1988, Canova and Ciccarelli 2013,). The application of the PVARX model on the microeconomic level allows us to capture the interdependencies of multiple time series, take advantage from cross-sectional dimension and benefit from exogenous variables.

6.1. Interpretation of Results

Here we summarize the findings obtained from PVARX (1,0) model using estimation results, IRF and FEVD in the light of three main areas: social sciences and humanities (SSH; including Law, Phil1, Phil2, Theo, Econ, Cult, Soc and Educ faculties), life sciences (LSc; Agri, Bio and Psy) and mathematical and natural sciences (MNS; Chem, Geo, Inf, Mat and Phys), see Table 1 in the Appendix.

6.1.1. Social Sciences and Humanities We find a positive impact of academic funding on the current number of PUB for Econ, Phil1, Cult, Soc and Educ. However, we identify no such effects for Law, Phil2 and Theo. This may be caused by the fact that the research areas of Law, Phil2 and Theo generally attract less TPF than other fields of SSH (more information is available in the Supplemental material). Interestingly, the opposite case, i.e. the past productivity of researchers influences the likeliness of obtaining TPF, is true only for Econ with more effect seen in later periods.

The effect of TPE on CIT is significant only for Phil2 and Theo. This in combination with previous results suggests that Phil2 and Theo may produce research outcomes with higher visibility and acceptance among scientific communities with the same funding as other SSH faculties. Contrary to Payne and Siow (2003), we detect no negative influence of academic funding on the number of CIT for any faculty of the whole university. This may indicate that focusing on obtaining of external funding does not necessarily cause a decrease in the quality of PUB. On the other hand, we find significant negative effect of CIT on TPE for Econ, which continues to gradually decrease over time. This value is also the lowest for the whole university. For instance, one additional CIT in the previous year leads to a decrease in TPE of Econ by around 200 EUR, if all other variables are held constant. To justify this, one may suggest that researchers concentrating on producing high quality PUB have less time needed for attraction of TPF.

The IRF results show that additional TPE leads to even more TPE in the long-term perspective for all SSH faculties; the corresponding increase for Cult being the largest in the whole university. One can track a similar pattern for PUB. An increase in PUB by one shock increases PUB over next five periods. This is consistent with the FEVD results indicating that the most of the change in PUB is caused by the innovations in PUB.

Our further analyses suggest that the scientific productivity increases with the academic age for Law, Theo and Econ. Although, the academic age of researchers in Phil1 leads to a decrease in the number of PUB, it also causes an increase in TPE. This can be referred to the shift of focus over life time or other reasons.

6.1.2. Life Sciences Our results show a positive, significant impact of TPE on PUB for all LSc faculties. The error variance in PUB is partly accounted for by shocks in TPE for up to 4-step ahead predictions. We also identify the positive influence of PUB on TPE over time and, furthermore, the slow but steady increase of TPE over time given a shock in PUB for LSc.

We find that TPE positively affects CIT for Agri and Psy and causes further sharp increase in CIT for Psy in a 5-year perspective given one additional innovation in TPE. This is consistent with the FEVD results for Psy, showing TPE as a driving force of change in the forecasting error variance in CIT in the long-term perspective. A possible explanation deals with the fact that after receiving a grant, the researcher needs time to carry out experiments, work thoroughly on the research problem and write a research paper. When the research work is published, it starts to collect CIT only after a certain period of time equal to the length of the citation window.

Interestingly, the variation in PUB explains almost half of the change in CIT for Bio, which is similar to the pattern of Phys from MNS. A possible reason is that some areas of Bio and Phys may have PUB with nearly one hundred of co-authors. As a result, the researchers produce higher number of PUB, which generate higher number of CIT. Regarding the academic age, the results are consistent with the previous literature. The age of researchers negatively affects the number of PUB (for Agri and Bio) and TPE (for Agri).

6.1.3. Mathematical and Natural Sciences Researchers of MNS with more funding produce more PUB and those who publish more attract more TPF. The only exception is Mat, where we discover no significant dependence between TPE and PUB in both directions. A shock in PUB has a positive impact on TPE during the next five years for all MNS faculties. Similarly, the TPE innovations lead to increase in PUB. Furthermore, for Phys the influence of change in TPE on PUB is the highest for the whole university. A high proportion of error variance of PUB for Geo is explained by shocks in TPE. This value is also the largest among all faculties. For Chem, innovations in TPE account for the change in PUB to a smaller extent.

External funding has a positive influence on the number of CIT for Chem, Geo and Mat. This is further supported by FEVD for Geo and Mat, as the variance in CIT is explained to a smaller extent by a variation in TPE. The fact that for Mat the TPE cause an increase in CIT but are not significant for the number of PUB suggests that academic funding supports the higher quality of Mat PUB, but not necessarily their quantity.

The academic age of researchers influences PUB and TPE of MNS differently in the sense of both significance level and the sign of the effect. The detected impact of academic age on TPE is positive for Inf and Phys, but negative for Chem. Interestingly, for these faculties the impact of age on PUB has an opposite sign, i.e. negative for Inf and Phys and positive for Chem.

All results clearly show the difference between analyses of the faculties and suggest that performing analyses on the high aggregation level of universities does not reflect the behavior of its faculties.

6.2. Implications for Policy and Decision Making

The differences in research fields pose a significant challenge for any policy maker, as the decision influences the whole university. Following our results, the reaction of a single faculty to an exogenous shock may be different from the reaction of other faculties or the effect seen on the aggregated university's level to the same shock. Therefore, the possible consequence of using this university-level information for the setting of incentive mechanisms may be a significant shift in the reacting behavior of researchers.

In the wake of the rise of new public management, universities increasingly use research performance measurements for the design of incentive-based motivation. A vivid example is performance-oriented budgeting that, among other targets, aims to stimulate attraction of more TPF and PUB in peer-reviewed journals. The common equal-for-all policy may punish faculties with low need in TPF, publishing mainly in books and with a majority of PUB with a single author; humanities being an example. While areas such as high energy physics may produce less than the world average of the corresponding field, the quantity of the research outputs may be higher than in other fields. Thus, one expects here no additional motivation to produce more, as a result of the performance-oriented policy. Moreover, using the counting of PUB and TPE, which is not field-normalized, to assess the research performance may also have structural effects, such as increasing the number of fragmented PUB, risk aversion and shift of focus from quality to quantity (Hicks 2012, Butler 2003, Braun 1998).

Furthermore, the effects of field diversity may have a serious impact on the governance of a university. In particular, implementing structural reforms, i.e. merger or division of faculties, requires clear understanding of how close is the research between fields, how similar is the writing, publishing or citing behavior, how equivalent is the need in TPF, how intense is the cooperation between faculties and how strong is the interdisciplinary research involving areas of interest. Providing policy makers with data-driven analyses as provided here (and in the Supplemental material) regarding these issues should complement experts judgments and, as a result, enhance the quality of decisions.

6.3. Recommendations for University Research Management

Given increased complexity along with the availability of information that policy and decision makers use for university research management, the questions of how to distinguish the relevant data basis, which methods to use for its analysis, and how to visualize the empirical results in clear and understandable manner are of great importance.

Our findings confirm the significant difference between faculties of a university and corresponding research fields regarding publishing and citing behavior, amount of TPF and practices of their attraction. A comparison of key performance indicators across divisions is common practice for decision making in a managerial environment. In fact, using raw non-adjusted data captures the diversity of the groups, however, it may lead to false conclusions. We emphasize that university management should normalize the research performance indicators for decision-making involving comparison across fields. This may help to eliminate the potential effects of research areas and make the performance measurements suitable for the research management process. Whether to perform normalization with the world or national fields' average, depends on the goals of the policy.

A growing need for data-driven support for decision making involves an inextricably linked concern about the reliability of analytical results, which is affected by data quality. Publication and citation data sets, as a rule, originate from external databases (Scopus by Elsevier, Web of Science by Thomson Reuters, Google Scholar etc.) This creates a bias against disciplines with lesser coverage by bibliometric databases. An important question emerges from this consideration: to what extent can one rely on analyses for a specific faculty or discipline? The possible solution, to the authors opinion, deals with the establishment of internal bibliometric data management utilizing all published outlets of university members. This, firstly, helps to select the external bibliometric database with the best coverage for the university. Secondly, this provides an evidence about the proportion of covered PUB of researchers and, subsequently, of faculties in a selected database. Thus, the meaningfulness of performance indicators based on such internal database can be justified for each faculty.

Our work deals with information on full professorships and their labs. Including other factors, such as data about teaching, administrative and refereeing duties, into the model may improve its precision. Furthermore, using data of all scientific members of a university (associate professors, assistant professors, research assistants etc.) may lead to including more PUB in the data set, the possibility to capture more heterogeneity in the model and, as a result, to produce more accurate results.

Universities are a source of knowledge production. Industry benefits from cooperation with universities through the access to the i) knowledge pool; ii) qualified workforce; iii) latest analytical techniques, for instance, econometric methods and data mining. The practice of using scientific methods for the improvement of internal processes at a university itself is often underestimated. Analogous to the business company, a university generates a lot of data throughout its activities that represents a rich source of information for decision support. The internal data evaluation using advanced statistical, econometric and data mining techniques available at the research environment of a university is a step towards a better understanding of the current state, explaining the past and making forecasts or describing future trends.

While admitting the critical role of information for the governance of top-level research, the argument about the lack of a workforce to undertake the complex analytical job is still common. One possible remedy is a better use of available resources, i.e. establishing internal research projects involving university scientists or as a part of Bachelor, Master of PhD thesis. The possible data privacy issue should be, of course, accounted for, for example, by working with anonymized, encoded or aggregated data. Such a combination of unique data, vast methodological knowledge and veiled personnel resources, results in a synergy effect for managerial decision making promoting research excellence.

Throughout the paper, we use modern visualization techniques which help to display the complex relationships in an understandable form. Striving to facilitate the cooperation across disciplines and increase the international visibility, research policy makers require targeted informational support. The sankey plots allows us to understand the interdisciplinary structure of the faculties in an intuitive way. Although not a central aim of this paper, this visualization technique is further applied to check the internationality of the faculties, i.e. with which universities or institutions on the national or international level does every faculty cooperate (see the Supplemental file).

Quantitative analyses provide an important insight into academic collaboration and its productivity. Here, we suggest the use of the chord diagram, a graphical method generally used to display interrelationships of genome data, for mapping of the intramural cooperation structures across faculties. To achieve this, we use joint PUB and information about co-authors to identify and measure inter-faculty channels of cooperation. Equally, one can use research projects and information about principal investigators.

In summary, our results shed light on the complex interdependencies between TPE, PUB and CIT uncovered from individual level data. The findings from estimation results, IRF and FEVD support the idea that scientific areas have diverse structures. Policy making that affects heterogeneous faculties should account for specifics of individual fields and not only rely on university level indicators. Providing the visualization of sophisticated data facilitates an understanding of the current state and future trends in research performance, helps to sharpen the research profile of the university, and enables a focused approach toward research management. The combination of data-driven analyses with expert knowledge creates significant added value for strategic decision making and further improves the foundations for the successful research management of the university.

Supplemental Material

Supplemental material to this paper is available at [link]. Programming codes Quantlets are available at [link].

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Supplemental Material to the ”Is Scientific Performance a Function of Funds?”*

by Alona Zharova, Wolfgang Karl Härdle and Stefan Lessmann

A Data Description

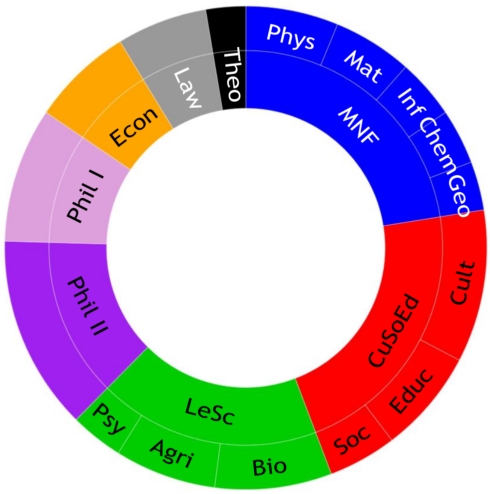

Figure 1: Sunburst plot for faculties and lower aggregation level. The width of segments corresponds to the number of professorships in each unit in 2015 (680 totally). The data of 8 outliers are removed.

TPE

Faculty	Per year						Total number
	mean	sd	min	max	skew.	kust.	of unique obs.
Law	75491	134579	-12064	962237	3.02	14	402
Phil1	117628	167645	-11495	1039790	2	11	330
Phil2	59907	83268	-201	413528	2	6	404
Theo	44405	67549	0	398130	2	10	275
Econ	111245	202180	-3828	1514808.01	3	16	414
Agri	164523	182954	0	856494	2	5	204
Bio	223043	338673	-8471	3007184	4	22	288
Psy	139689	110010	0	389293	0	2	81
Edu	98639	108938	0	405850	1	4	123
Cult	98746	223163	-2256	2051762	6	46	479
Soc	87138	127817	-393	563300	2	8	105
Chem	222662	278167	-258	2173382	3	16	219
Geo	95888	118846	0.00	581977	2	8	93
Inf	153125	222632	0	1171008	3	10	147
Mat	139733	158113	0	678933	1	4	161
Phys	276034	322817	-2099	2291122	32	13	219

Table 1: Descriptive statistics for third-party funds

*The R codes to the corresponding analyses and visualizations are provided in GitHub (Link tba)

PUB

Faculty	Per year (mean)	sd	min	max	skew.	kust.	Total number of unique obs.
Law	1.56	1.23	1	9	3.17	15.35	131
Phil1	1.79	1.50	1	11	2.53	10.39	359
Phil2	1.60	1.05	1	9	3.25	18.48	231
Theo	1.80	0.99	1	5	1.31	4.57	144
Econ	2.55	2.14	1	14	2.37	9.48	307
Agri	4.65	4.04	1	19	1.26	3.92	377
Bio	5.07	4.66	1	38	3.25	18.99	684
Psy	5.34	4.20	1	21	1.29	4.62	184
Edu	3.79	3.29	1	17	1.22	3.97	140
Cult	1.43	0.86	1	8	4.08	26.04	329
Soc	1.99	1.36	1	9	1.98	8.12	138
Chem	8.44	6.03	1	31	1.02	3.70	432
Geo	4.14	4.25	1	24	2.15	8.20	191
Inf	4.73	3.50	1	16	1.21	3.90	200
Mat	3.59	3.21	1	16	1.69	5.50	261
Phys	16.02	21.33	1	166	3.85	20.80	488

Table 2: Descriptive statistics for publications

CIT

Faculty	Per year (mean)	sd	min	max	skew.	kust.	Total number of unique obs.
Law	7.02	16.91	0	152	5.77	45.09	131
Phil1	5.59	11.63	0	110	4.89	34.17	359
Phil2	7.00	15.49	0	98	3.50	16.25	231
Theo	1.35	2.48	0	11	2.95	11.52	144
Econ	33.41	51.95	0	347	3.17	14.98	307
Agri	89.62	184.21	0	1390	3.88	20.99	377
Bio	188.84	238.39	0	1710	2.79	12.98	684
Psy	117.36	133.34	1	1052	2.85	16.35	184
Edu	52.77	77.96	0	294	1.75	4.99	140
Cult	4.62	19.69	0	231	8.20	81.82	329
Soc	23.14	56.18	0	521	5.88	47.63	138
Chem	265.86	305.05	0	2639	2.82	15.58	417
Geo	112.17	232.74	0	1706	4.39	25.51	191
Inf	40.06	58.23	0	307	2.18	8.24	200
Mat	81.98	192.23	0	1642	5.36	38.21	261
Phys	477.81	831.19	0	8284	5.40	45.26	488

Table 3: Descriptive statistics for citations

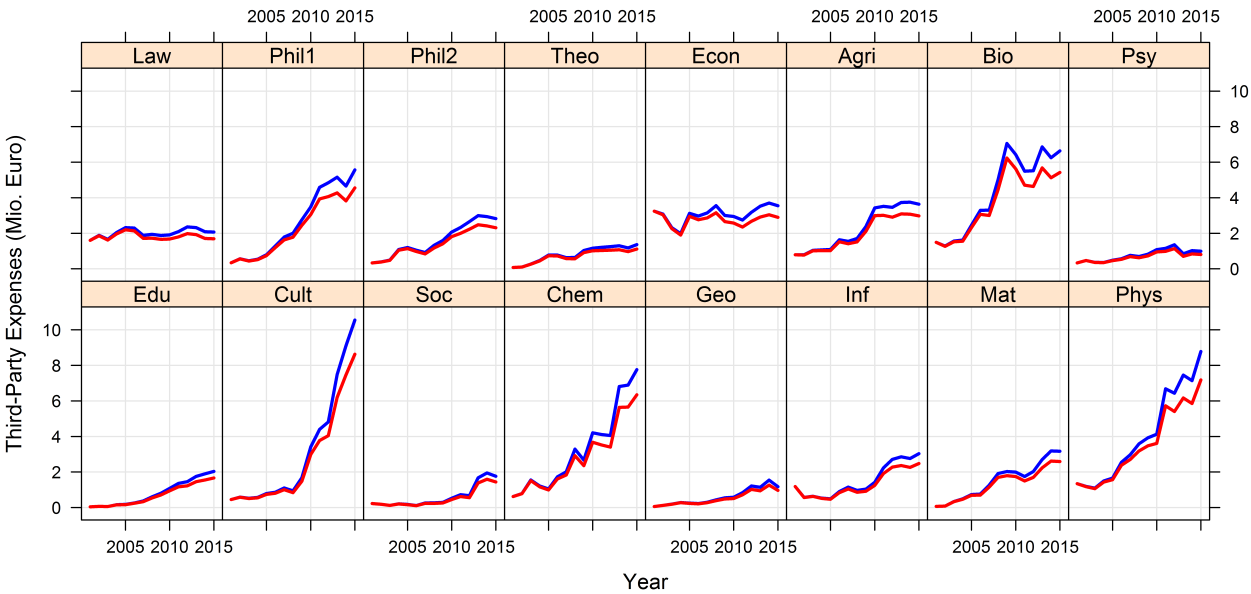

Figure 2: Total amount of TPE of professorships from 2001 to 2015. The data of 8 outliers are removed. The nominal value (blue) and the inflation adjusted real value (red).

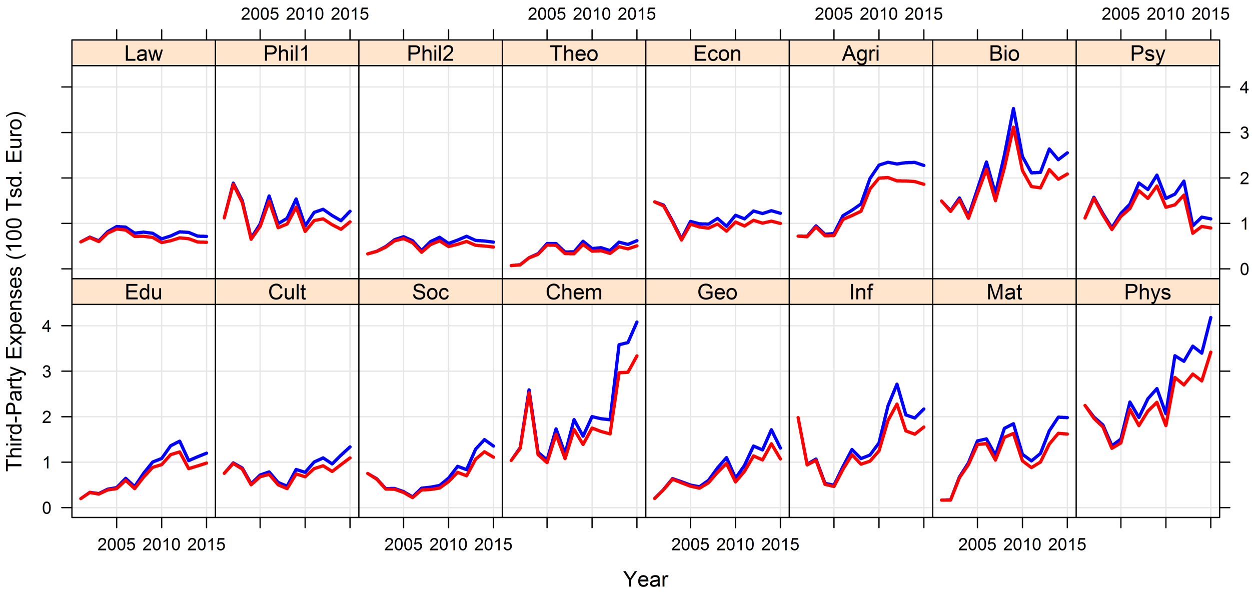

Figure 3: The development of nominal (blue) and inflation adjusted real (red) TPE in relation to the number of professorships with TPE within each faculty from 2001 to 2015 without 8 outliers.

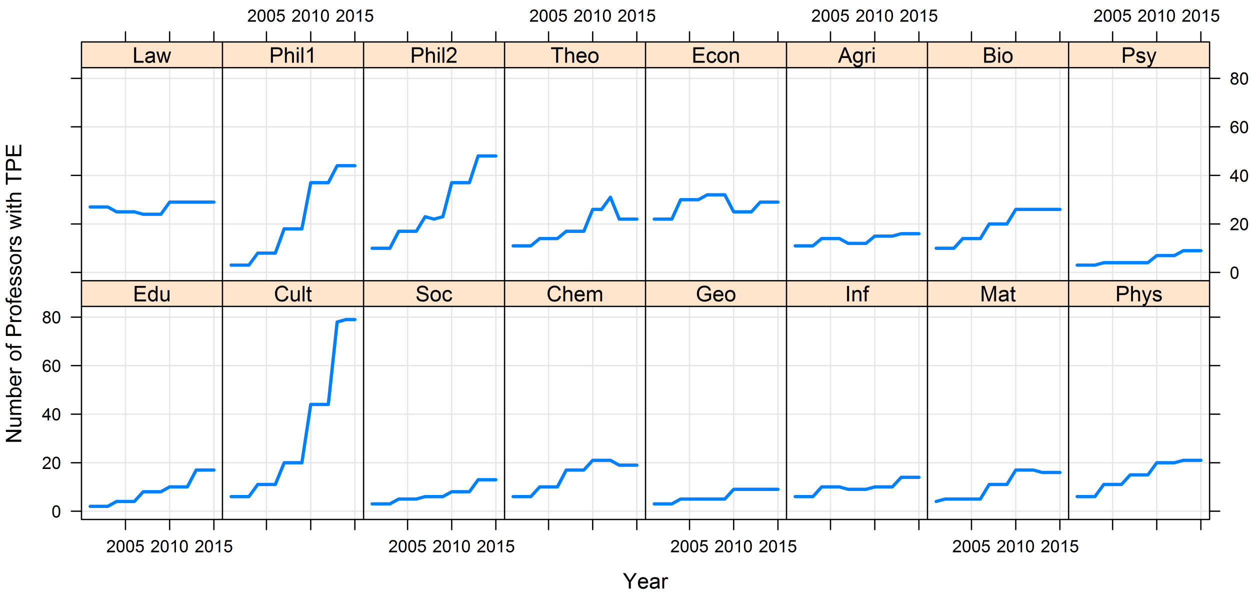

Figure 4: HU professors with TPE through the faculties from 2001 to 2015. The data of 8 outliers are removed.

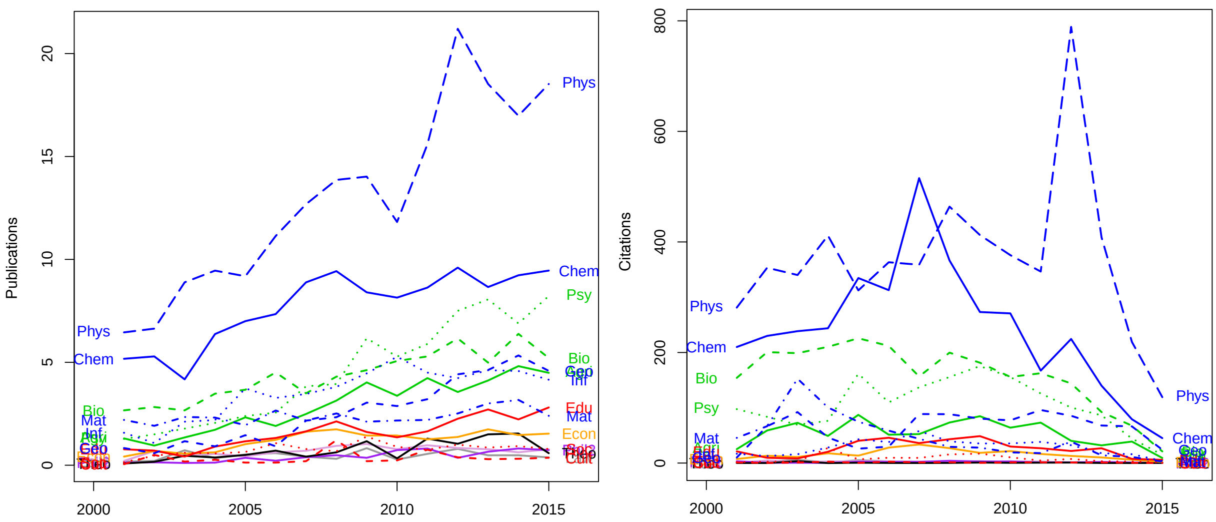

Figure 5: Publications (left) and citations count (right) per person for faculties from 2001 to 2015 without 8 outliers. Citation window equals three years.

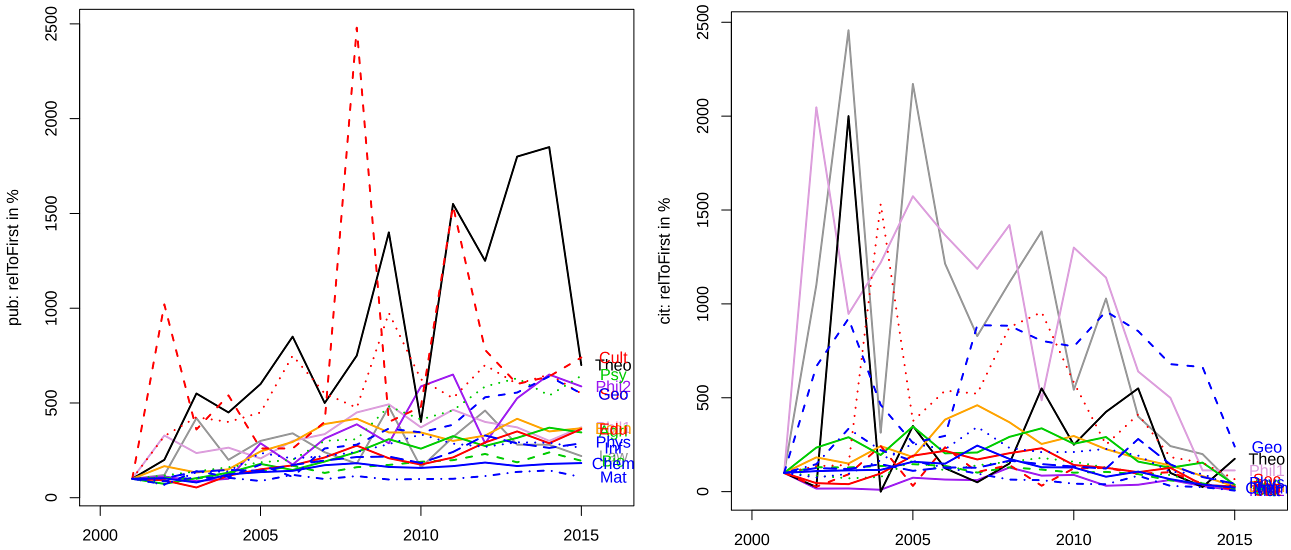

Figure 6: Publications (left) and citations (right) growth rate relative to the values 2001 for professorships from 2001 to 2015. The data of 8 outliers are removed.Citation window equals three years.

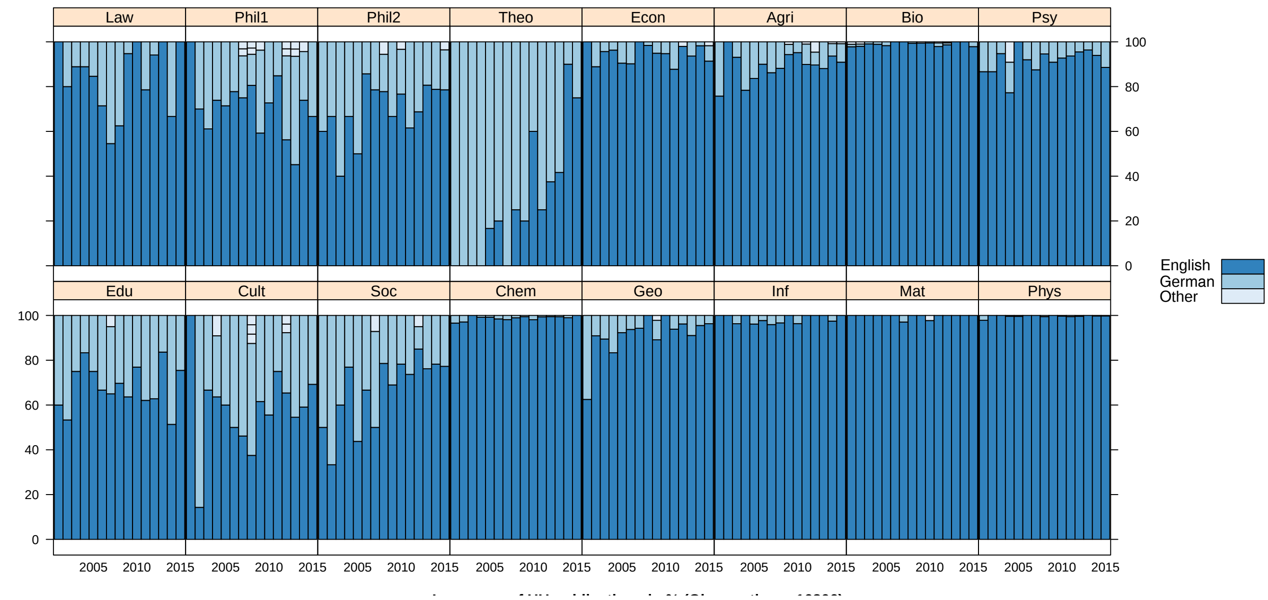

Figure 7: Proportion of languages (EN – dark blue, DE – blue, others – light blue) of all publications in corpus from 2001 to 2015. The data of 8 outliers are removed.

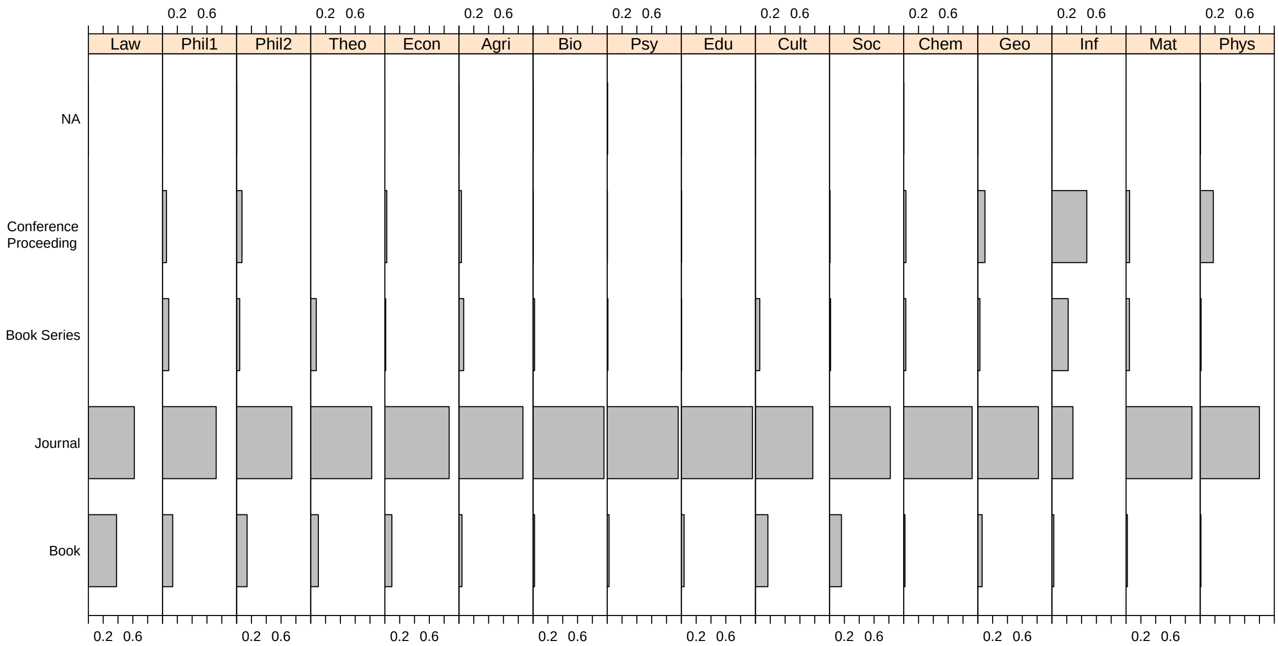

Figure 8: Frequency of publications of each document type published by professors grouped by faculties from 2001 to 2015. The data of 8 outliers are removed.

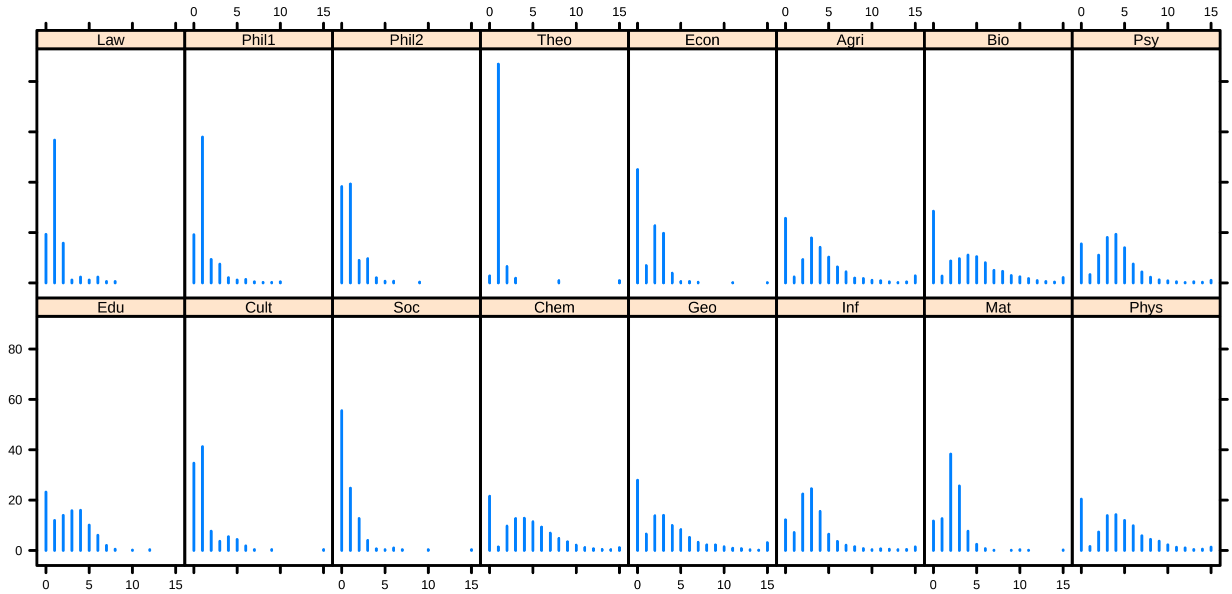

Figure 9: Distribution of publications according to the number of authors from 2001 to 2015. The data of 8 outliers are removed.

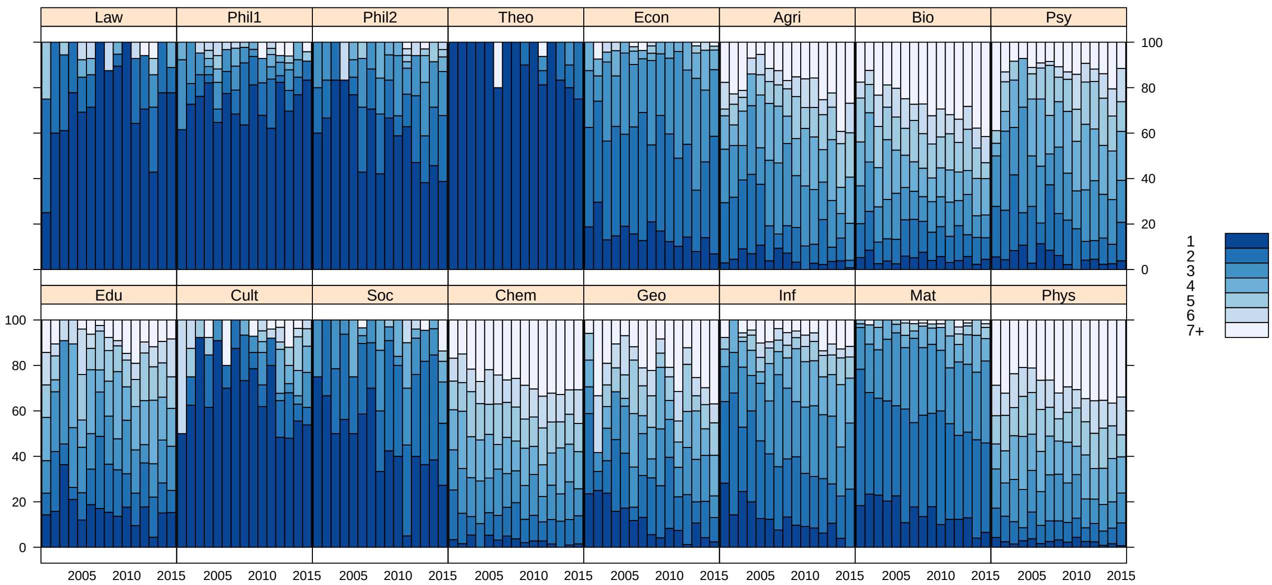

Figure 10: Proportion of number of co-authors (from 1 – dark blue, to >7 – light blue) of publications within faculties. The data of 8 outliers are removed.

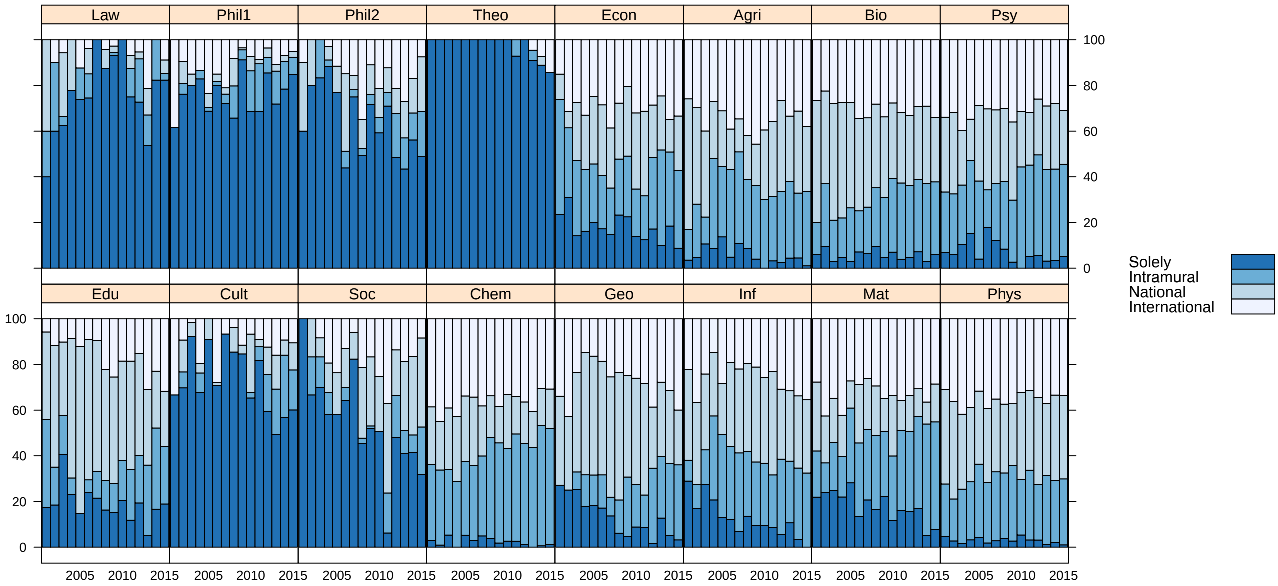

Figure 11: Dynamics of cooperation from 2001 to 2015 in percentage: solely authorship (navi), multiple inside HU – intramural (dark blue), national (blue) and international (light blue). Fractional counting of publications is used. The data of 8 outliers are removed.

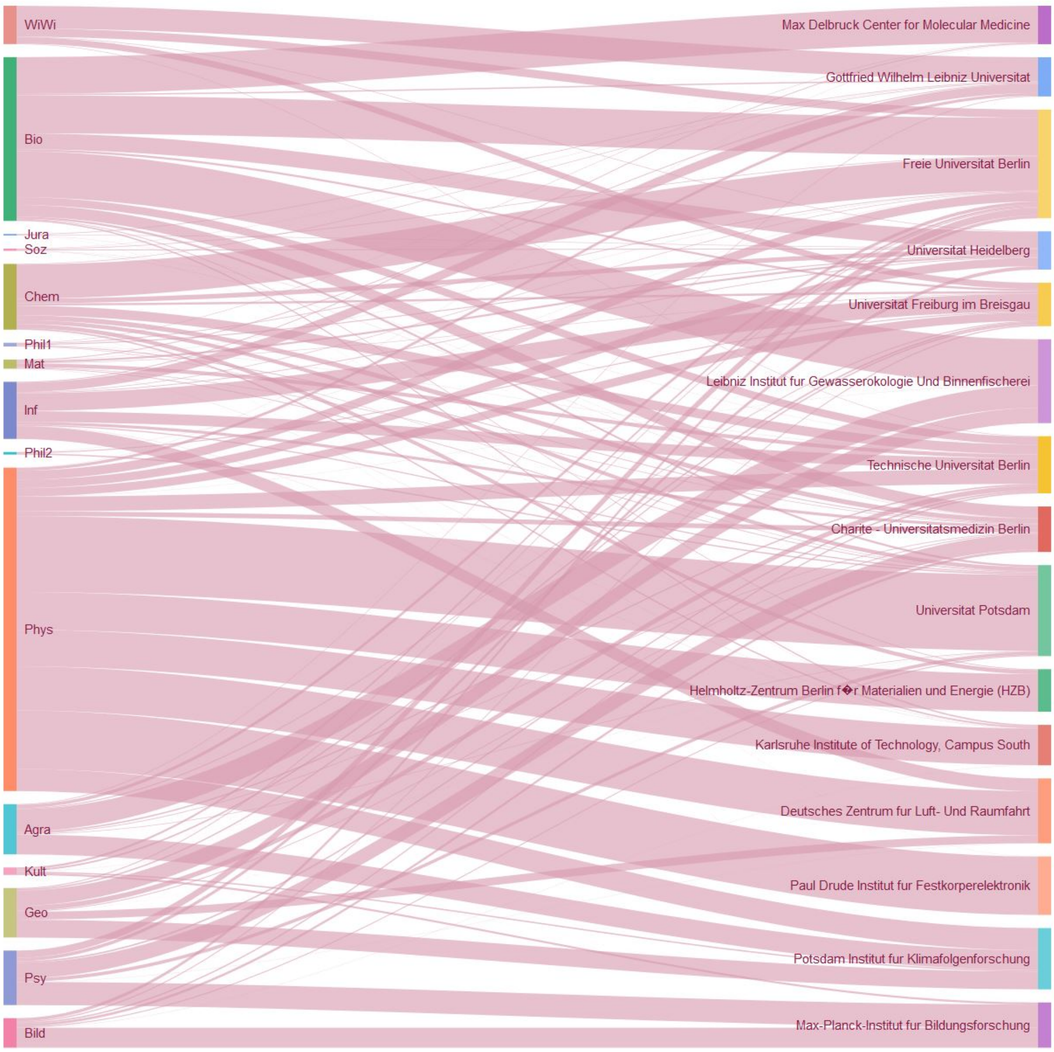

Figure 12: National cooperation: Sankey plot for faculties (left) and other German institutions (right), with more than 70 publications, fractional counting. The data of 8 outliers are removed.

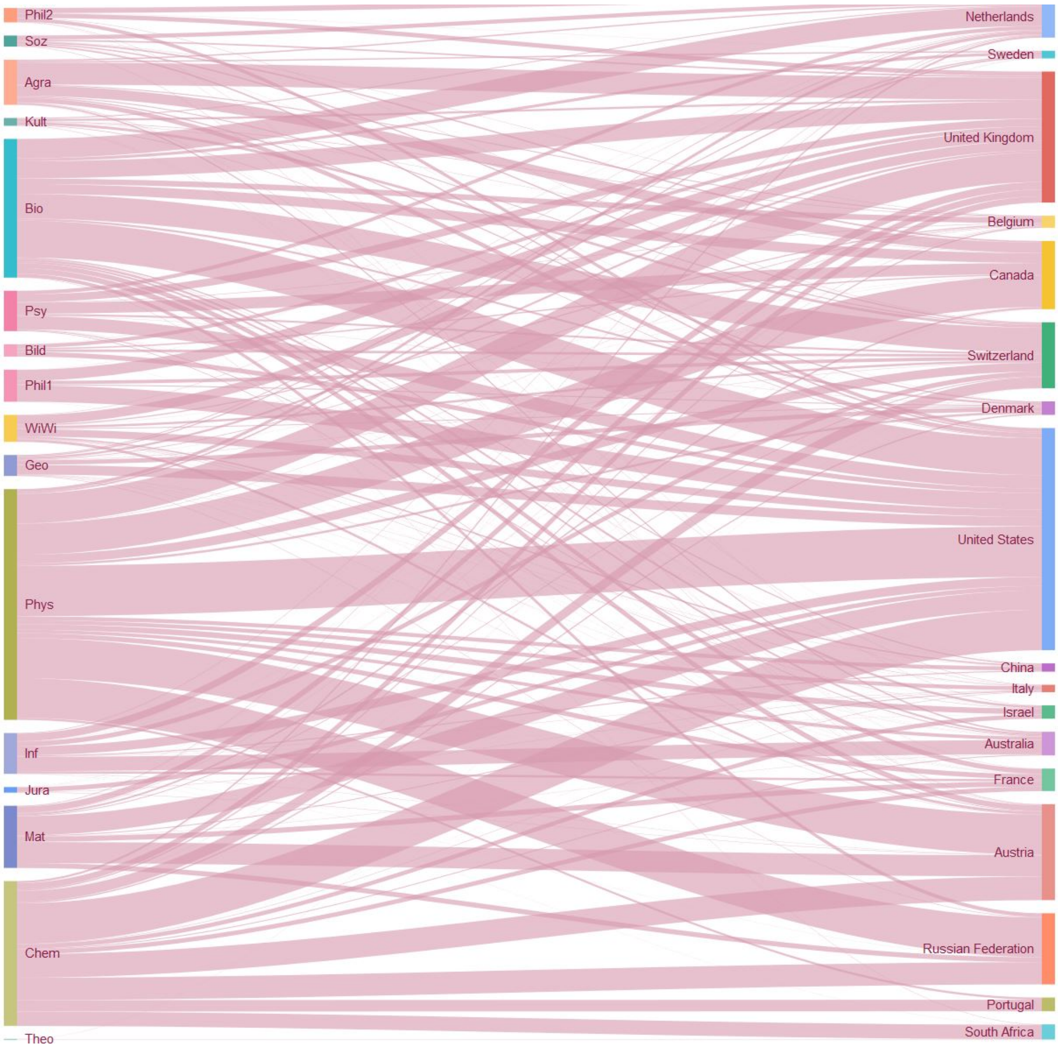

Figure 13: International cooperation: Sankey plot for the cooperation between HU units (left) and other countries (right) for 2001–2015, without Germany, fractional counting. The data of 8 outliers are removed.

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