SNSF Starting Grant 2014
Research proposal

Section a. State-of-the-art and objectives

Overview, innovative scope and interdisciplinary nature of the proposal

There is a strong trend towards more co-authorship in all disciplines. This has been demonstrated in case studies in the social sciences (Fisher et al., 1998; Babchuk et al., 1999; Moody, 2004) and natural sciences (Laband and Tollison, 2000). In an overarching analysis, Wuchty et al. (2007) show with 19.9 million papers and 2.1 million patents across more than 200 disciplines that "research is increasingly done in teams across nearly all fields" (p. 1036). The trend is strongest for the sciences and engineering, where 80 % of the articles are written in teams. In the social sciences, half of the articles and in Arts and Humanities 10 % are written collaboratively. There is an increasing trend, however, in all domains (Wuchty et al., 2007).

The increasing dominance of teams may have structural reasons such as an increase in the number of academics, making it easier to find suitable collaborators and in better communication technology (Hudson, 1996). It may also be triggered by increasing specialization, making it more efficient to divide labor (Moody, 2004). The increased pressure to either publish or perish may also explain the rise of co-authorships (Shapiro et al., 1994). While the fact of the rise in co-authorships are well understood, its consequences are subject to research and debate.

This proposal outlines a unified framework of how social norms contribute to cooperation in scientific collaborations. It builds on the applicant's theory of normative conflicts and derives positive and negative consequences of collaborations in science. On the one hand, norms of prosociality can promote collective good provisions such as sharing data, joint writing and division of labor. Yet, normative conflicts can emerge from asymmetries between invested time and effort and its outcomes in reputation and prestige. Further, teams may be more prone to norm violations and scientific misconduct.

The research design considers a triangulation of three different quantitative research methods to overcome their individual limitations and provide a comprehensive understanding. Project A analyzes scientists' "objective" behavior by bibliometric data, allowing the estimation of different disciplinary name ordering norms, normative change and normative conflicts. While sparse, this data yields high-stake behavior without social desirability. Project B analyzes scientists' "subjective" attitudes, beliefs and reported behaviors in surveys. While fine-grained, this is limited by misreporting. Project C uses meta-analyses for estimating the extent, trend and disciplinary differences in publishing biased and fake data. This design requires big data, but overcomes misreporting.

This research methodology goes far beyond what is typically done in sociology because of three reasons. First, scientific collaborations are not only investigated in sociology, but over a large variety of disciplines, including sciences, engineering, social sciences, arts and humanities. Second, the hypotheses are developed from general game theoretical models. These models are state of the art in the newly evolving fields "behavioural economics" and "experimental game theory" and are not (yet) common ground in sociology and rarely been applied to sociology of science. Third, the empirical methods in part A consider "big data" analysis of the Web of Science data base, containing over 46 million articles over 241 disciplines. This requires statistical programming and advanced data processing, which is more common in computer science than in sociology. The applicant has expertise in all three fields. This is rare among sociologists and the combination of all three methods reflects a research strategy with high risk, but also high potential to gain a more comprehensive understanding of scientific collaborations, teamwork and conditions for cooperation more in general.

Advantages of teamwork

Teams have the advantage that scientists with different skills and strengths can work together. They can contribute expertise in different methods and knowledge of different theories and branches of literature. Researchers in teams can also discuss more intensively, brainstorm more effectively and come up with novel ideas and viewpoints. More interaction may also contribute to eliminating weaknesses with respect to methods, theory and interpretation.

One way of quantifying these advantages of teamwork is the so-called wisdom of crowd effect (Surowiecki, 2004; Rauhut and Lorenz, 2011; Lorenz et al., 2011). The more people, the larger the opinion diversity in the team. The majority or average opinion is often better than expert opinions so that sharing and aggregating information from many people often yields better results compared to working alone. Wuchty et al. (2007) show that such a wisdom of crowd effect seems to work in scientific teams as well, since multi-authored scientific articles receive more citations compared to single-authored ones. This positive effect in citations is robust across natural sciences, social sciences and humanities.

The citation advantage of teams may not only be rooted in better manuscripts, but also in better networking and marketing. When the link between citations and quality is not questioned more fundamentally (Aksnes, 2006; Bentley, 2007), it could be argued that citations are an inherent network measure and may partially represent networking and marketing efforts rather than quality. For example, articles written by larger co-author groups may have more proponents and more authors can make more marketing for their research findings at different conferences or through other communication channels. Hence, more co-authors may generate a larger familiarity of the article within the scientific community, generating more citations due to networking rather than quality (Valderas, 2007).

Disadvantageous teamwork and cooperation failures

Whereas teams have certain advantages in producing scientific knowledge, they are also prone to problems of collective action. While the division of work and cooperation in research teams is becoming an important part of scientific production, the reward and career system is still on an individual basis, creating a paradox (Mangematin, 2001).

A multi-authored scientific publication can be regarded as a collective good in the sense of Olson (1965). Often, academics decide early on whom to include as an author of a publication. Once the authors are agreed upon and a joint article is planned, everybody may hope that the others will do the work. Such free-riding on others' contributions is often reported as a major problem in scientific collaborations (Garfield, 1995). It is rarely the case that authors are excluded from a publication during its time-consuming production process (Bhopal et al., 1997). However, all authors can freely consume the scientific credit from the joint publication in terms of receiving citations, improving chances of promotion and enhancing one's scientific reputation. It is known since Olson (1965) that group size is a relevant predictor of individual contributions to public goods. This can be applied to co-authorship, where the relation of individual contribution efforts to joint article and its collective benefits in terms of improvements becomes smaller, the more authors collaborate on a paper. Hence, each co-author may contribute less for each added member to a research team.

Power relations between co-authors play also a crucial role. Free-riding may emerge from the "principle of least interest" (Waller and Hill, 1951). Professors with many publications on their vita have a smaller benefit from each additional publication compared to their students with fewer publications. This may generate asymmetric contributions of professors, who free-ride on doctoral students' work. Relatedly, tenured collaborators may have a longer temporal horizon and act slower. In contrast, those without tenure may try to progress as fast as possible to exceed the threshold of having enough publications to receive tenure. These asymmetries in working speed can also cause free-riding (Schwartz, 1974; Jackson and Wolinsky, 1996).

Cooperation failures may also arise from different individual expectations regarding appropriate contribution levels. Such different contribution norms are especially problematic in interdisciplinary collaborations, where co-authors often have different expectations of how much effort and time is fair in a given author constellation (Maciejovsky et al., 2008).

Social norms as mechanism for cooperation

Olson (1965) argues that cooperation failures can be overcome by so-called *selective incentives*. Selective incentives motivate actors to contribute to collective goods, because they bridge the conflict of interests between individuals and group.

Social norms are a well known selective incentive for the provision of collective goods (Coleman, 1990). Broadly speaking, social norms are imperatives which prescribe specific actions in social situations, whose violations are often punished. More precisely, a social norm can be defined "as a commonly held expectation of how an actor ought to behave, which is enforced by sanctions in case of violations." (Winter et al., 2012, p. 920 f.). Social norms can promote cooperation and increase the group's welfare by proscribing the contribution to collective goods such as jointly planning research projects, contributions to funding, designing and conducting research, analysis of data and writing.

On a more theoretical level, two factors can explain why social norms contribute to collective good provisions. Actors may have internalized the social norm to such a degree that they may willingly adhere it. In sociology, Winter et al. (2012) call this the "level of normative commitment". In social psychology, this mechanism is called "social value orientation" (Van Lange, 1999) and in economics, social preferences (Fischbacher and Gachter, 2010). On the other hand, actors may follow social norms because they fear sanctions in case of violations (Ostrom et al., 1992; Fehr and Gächter, 2000). In this way, even egoistic actors who are not willing to freely adhere to the norm may behave as if they were norm followers because they believe that there are enough others who are willing to punish non-compliance.

Since social norms can promote the provision of collective goods, the crucial question is under which conditions they emerge. One condition for the emergence of social norms is that the involved actors expect future interactions with the same people in similar situations. The prospects of future interaction has also been called *shadow of the future*. Even egoists would contribute to collective goods if the probability of future interactions is sufficiently high. The main idea is that the gains from future mutual cooperation can be higher than the gains from exploiting the other person one time and never interact again (see Axelrod, 1984).

Transferred to cooperation problems in research teams, the shadow of the future argument implies that fruitful scientific collaborations emerge if team members expect others to stay in science, to stay in their field of expertise, to have still enough time in the future and to be willing to collaborate on future joint projects. As Bidault and Hildebrand (2012) put it: "The implication would be that co-authorship pays off over the long-term and that rather than changing academic partner repeatedly, co-authors would be well advised keeping the same partner over an extended period of time."

A second mechanism for the emergence of cooperation norms is the *shadow of the past*. This mechanism can work in direct reciprocal relations among collaborators. Gaining experiences step by step over time enables collaborators to learn how cooperative the partner is and how much she or he values mutual work (Gulati, 1995). In addition, sanctions of uncooperative behavior may help clarifying joint expectations and smooth the way for ongoing joint work (Macaulay, 1963). For the case of scientific collaborations in economics, Bidault and Hildebrand (2012) find that co-authors with more joint articles in the past reach more citations with their joint articles.

The shadow of the past is not only limited to direct experiences among the involved actors. Information about cooperativeness can also diffuse to third parties. Having the reputation to be a cooperative type fosters collaborations even among actors who do not yet know each other (Raub and Weesie, 1990). Applied to collaborations among researchers, scientists can signal their cooperativeness and productiveness through their number of publications and size of their co-author network. In this view, authors would preferentially choose those researchers as new collaborators who have published many articles with many co-authors. This kind of *preferential attachment* may, however, generate large inequality in scientists' co-author networks (Merton, 1968; Barabási et al., 2002; Newman, 2004).

A theory of normative conflicts and its application to co-authorships

An often taken-for-granted view on social norms is that they have positive effects for society and promote cooperation, as described by the arguments above. Social norms have a double-edge, however. On the one hand, they may promote cooperation, on the other, they can generate conflicts. The perspective of normative conflict is central to this proposal, whose building blocks I have jointly developed with Fabian Winter in a series of publications (Rauhut and Winter, 2010; Miller et al., 2011; Winter et al., 2012). The main problem here is not to overcome self-interest but to agree on the norm which should be followed. Normative conflict can be defined "as the transaction failure resulting from actors holding partially (at least) exclusive normative expectations" (Winter et al., 2012, p.921).

Normative conflicts can easily emerge in teamwork, where labor is divided and members are concerned about distributional justice. A crucial question is how to balance each member's inputs in terms of time, effort, energy and other kinds of investments and the output in terms of wage, reputation, prestige or promotion prospects. Homans (1961) proposed an *equity norm*, for which "the received benefits of a group member should be proportional to her investments" (Homans, 1961, p. 237).

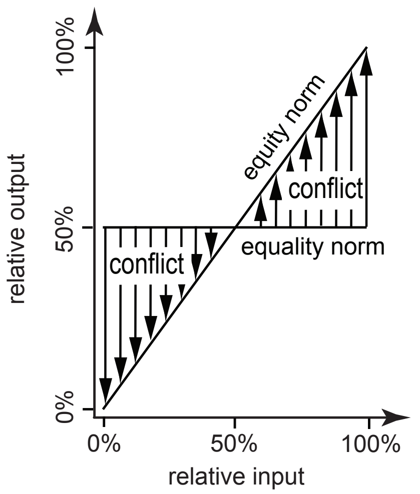

Fig 1. Schematic representation of normative conflicts between team members holding different distributive justice norms (Figure based on Winter, Rauhut and Helbing (2012)).

However, the dilemma is that people "differ in their ideas of what legitimately constitutes investment, reward, and cost, and how these things are to be ranked" (Homans, 1961, p. 246). This may create transaction failures when several parties disagree due to their different conceptions of distributive justice. An alternative norm of distributive justice is the *equality norm*. This distributional principle states that joint work should be divided equally, so that actors' different contributions to the good should be disregarded. In particular, when team members and collaborators interact over a long period of time, equality norms can generate harmony and group identity (Leventhal et al., 1980). This norm is often applied when team members are not too different with respect to need, status or investments in a project.

Both equity and equality norms can solve cooperation problems in work teams. In the case of equal contributions to a joint project, both have the same implications: outcomes are to be split equally. However, if inputs are different, both norms imply different allocations. A low contributor claiming equal shares would not agree on getting only his input share. However, someone with an equity norm who contributed larger amounts would not agree on handing over more than the other's input share. In this case, cooperative intentions are not enough to reach a cooperative solution. Normative conflicts can easily emerge in research teams, where team members may have different views on how to relate inputs in terms of effort, time, ideas and methodological know-how to outputs in terms of author positions, reputation, career prospects, research money or salaries.

Normative conflicts about name ordering

One application of normative conflicts to scientific collaborations is the problem how to order names on articles. This can have serious consequences. Einav and Yariv (2006) have shown for economists that "faculty with earlier surname initials are significantly more likely to receive tenure at top ten economics departments . . . , and, to a lesser extent, are more likely to receive the Clark Medal and the Nobel Prize" (p. 175).

Zuckerman (1967) found in interviews with Nobel laureates that they make strategic career choices regarding their author position. Before receiving the price, they try their best to receive first authorship to become famous. After having received the price, they often change to a "noblesse oblige norm" and prefer later author positions. While in modern psychology, for example, most authors order names non-alphabetical (Spiegel and Keith-Spiegel, 1970), in economics, name ordering is mainly based on equality and done alphabetically (Van Praag and Van Praag, 2008). In medicine, for example, two norms co-exist (Shulkin et al., 1993): first authorship, favoring the main contributor, and last authorship, favoring the principal investigator.

The double-edge of punishing uncooperative collaborators

Norm adherence and social value orientation may not be enough to promote cooperation in scientific work teams. Still, scientists may fear that collaborators perform their work sloppy, the others' work is wasteful or even fraudulent and may damage one's reputation, shared materials or data is destroyed, own ideas are exploited or confidentiality agreements are broken. A crucial question is whether punishment of uncooperative behavior in research teams works to enforce cooperation?

One kind of punishment can be the threat to withhold future cooperative behavior (Blais, 1987). However, junior scientists are often caught in a relationship and their threat to end the relationship is often not credible since they have much more to lose than their advisors or other senior faculty (Frost-Arnold, 2013). An alternative may be centralized sanctions. For example, scientists may appeal to journals, heads of their departments or to the ombudsman at their institution if collaborators have stolen their ideas or claim inappropriate co-authorship. However, junior scientists with little power and reputation may fear retaliation of senior scientists. They may also have less credibility due to their lower standing and less experience or they may depend financially on their supervisors, inhibiting formal sanctioning (Wagena, 2005).

A novel way of enforcement are written agreements about authorship roles, division of labor and how data, knowledge and ideas are going to be shared – so-called "prenuptial agreements" (Gadlin and Jessar, 2002). However, many scientists are uncomfortable with written agreements. Even proponents of prenuptials "recognize that using scientific prenuptials goes against the informal norms of science" (Gadlin and Jessar, 2002, p. 12). Rigid regulations and formal statements can stand in stark contrast to creativity, brainstorming and the sometimes chaotic and unpredictable development of research projects. It is open to research, whether scholars will increasingly accept written contracts for their collaborations and how they are best designed to keep up motivation and trust, but also enable enough control and predictability.

Importance and impact of the proposed research program

This project contributes to a better understanding of the structural conditions of good scientific teamwork. Due to the dramatic change from solitary researchers to teamwork in virtually all disciplines, we need robust knowledge how sustainable cooperation in research teams can be achieved. This knowledge is relevant for all disciplines.

The planned contributions to knowledge range from academic insights to practical applications. From a practical point of view, the project will reveal which team compositions of "lone fighters" and "team players" work best for which team sizes in which disciplines. Moreover, the project will yield new insights in flexible ways of conflict resolution. It will be shown in which situations written agreements, such as contract-like "prenuptials" about ressource sharing and labor division are recommended and when it is better to trust on informal agreements and incomplete contracts. Recommendations will be developed about the most productive, fair and accepted name ordering norms for different fields, different team sizes and for joint work between supervisors and their Ph.D. students. These novel insights will also help in developing Ph.D. regulations at universities. Empirical knowledge is also needed for organizing team work in Ph.D. programs to yield favorable learning environments and productive knowledge transfer between supervisors and students.

Apart from these practical and political contributions, the project yields a novel theoretical understanding of how social norms and cooperation are interlinked. While the current state of the art emphasizes the positive aspects of social norms on cooperation, this project sheds novel light on the negative facets. Actors adhering to different norms can experience normative conflicts, which undermine cooperation despite all good intentions. One example is interdisciplinary teamwork, where some collaborators insist on alphabetical name ordering and others on effort-based principles. While both principles may be perfectly fine on their own, their clash can cause severe conflicts. These basic insights are relevant for sociology, political science and economics, where "behavioral" theories of strategic interaction receive increasing attention and may become the new explanatory building blocks of the disciplines.

Furthermore, the project contributes to organizational sociology, labor economics and management. It will be investigated in which organizational settings prosocial people, who care about own and others' well-being, have better career chances and when individualistic ones do better, who only care about themselves. Also novel insights for the functioning of different distributional justice principles in different organizational settings will be attained. This contributes to understanding under which conditions effort-based reward and wage schemes generate higher outputs and when equality-based principles.

Section b. Methodology

Combination of three research methods to overcome their individual limitations

The methodology section elaborates how to analyze and measure social norms, cooperation, conflicts and misconduct in the production of scientific knowledge. The proposed methods combine three quantitative data sources, subsequently called projects A, B and C. This combination yields a comprehensive data set (Fig. 2). The reason for combining different data sources is that they have different strengths and weakness so that their composition can complement their limitations and combine their potency.

Project A analyzes "objective" scientists' behaviors by using the bibliometric data source Web of Science. This data allows the estimation of different disciplinary name ordering norms, normative change, normative conflicts in teams, effects of disciplinary norms on inequalities in scientists' career chances, in their publication strategies and their network formation. The strength of this data set is that it captures actual behavior. It is not biased as reported behavior in surveys, where scientists' may have distorted memories of their behaviors, may not admit socially undesirable behaviors or attitudes or may exaggerate their cooperativeness or norm adherence. The limitation is the sparseness of the data. It mainly consists of the number of co-authors on articles, their order, the disciplines and journals and the citations and bibliographies, enabling network and citation analyses.

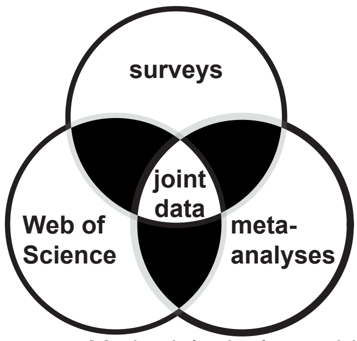

Fig 2. Methodological combination of surveys ("subjective" attitudes, beliefs, reported behaviors) with "objective" behaviors in bibliometric data and meta-analyses of published statistical results.

Project B analyzes scientists' "subjective" attitudes, beliefs and reported behaviors in surveys. The advantage is that this method yields more fine-grained information about the causes and consequences of cooperation, norms and punishment of uncooperative collaborators. A limitation is that this data may be subject to misreporting and social desirability bias. One way of limiting this bias is the elicitation of scientists' social value orientation by using monetary payoff divisions among the participants, yielding incentive-compatible behavioral data.

Project C analyzes actual behavior regarding scientific norm violations in an indirect way to overcome the problem of social desirability in surveys. The extent, trend and disciplinary differences of publishing biased or fake data will be analyzed by collecting a large number of reported test statistics from journals articles in different fields. The strength of this approach is that it is not biased by scientists' whitewashing and denials. The limitation is that a large number of articles is needed to detect publication bias and fake data.

Project A: Distributional justice norms in team publishing

Publications have enormous influence on the academic career of scientists. One major problem of working together is how to signal different contributions to joint publications and how to fairly share the credits for teamwork. One way of signaling proportional contributions is the ordering of names on articles. Due to different name ordering norms in different fields, this can have substantial consequences for interdisciplinary teamwork.

Basic assumption 1 (norm heterogeneity): *There is large heterogeneity in name ordering norms in different disciplines.*

There is little research on investigating name ordering norms over all fields of science. This lack of research is described by Frandsen and Nicolaisen (2010, p. 608) who assess that "longitudinal studies of trends and tendencies in various disciplines are few. Studies combining credit assignment practices with trends in multi-authored publications . . . are even fewer." One major problem has been to cope with the large amounts of bibliometric data available. As Lazer et al. (2009) point out, "the capacity to collect and analyze massive amounts of data has transformed such fields as biology and physics. But the emergence of a data-driven 'computational social science' has been much slower." (p. 721). The Thomson Reuters Web of Science data base provides the opportunities to conduct such large-scale investigations of authorship norms over all fields of science. It consists of over 46 million articles, subdivided into 241 disciplines. The data contains names, name ordering and number of co-authors on papers, journals and bibliographies. This also allows the construction of citation data and co-author networks.

Only recently have scholars conducted broader analyses over longer time spans and across a large range of disciplines. Frandsen and Nicolaisen (2010) studied economics, information science and high energy physics. Waltman (2012) analyzed publication norms in all fields in the Web of Science database. He found that mathematics and economics are the fields with the strongest alphabetical norm and the use of alphabetical authorship is generally declining over time. One major issue in determining authorship norms is the distinction between intentionally and incidentally alphabetically ordered papers. In the case of two authors, there is a 50 % chance that a paper is alphabetically ordered, although the order has been intentionally based on merit or other principles. For the case of three authors, this probability is 17 %, and more generally, for n authors, the probability of an incidentally alphabetically ordered paper is $\frac{1}{n!}$ (Fig. 3). Taking this probability, one can estimate the rate of intentionally alphabetically ordered papers, i.e. the prevalence of an alphabetical norm in a field, by adjusting the rate of observed alphabetically ordered papers by the following correction formula (Rauhut and Winter, 2012; Waltman, 2012):

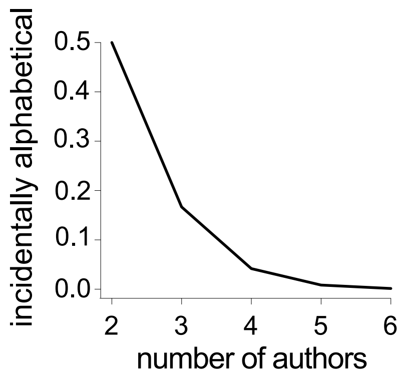

Fig 3. Probability of incidentally alphabetically ordered articles by group size (plot of equation 1).

$$\text{p(alphabetical norm)} = \frac{\text{alphabetical rate} - \frac{1}{\text{n!}}}{1 - \frac{1}{\text{n!}}} \tag{1}$$

Waltman (2012) used this correction formula and calculated the prevalence of alphabetical norms, however, regardless of the number of co-authors. Levitt and Thelwall (2013) conducted a more fine-grained analysis, differentiating by the number of co-authors, however, only for a small set of social science disciplines and a short time frame.

The first step in this project is the corroboration of the basic assumption that name ordering norms are largely heterogeneous in different fields. This assumption is crucial for many of the more specific hypotheses of the project. Furthermore, it is important to find enough empirical variation in name ordering norms so that constitutive hypotheses can be tested and some fields with enough empirical variation can be selected for inclusion in the survey of scientists (project B). Hence, it will be an intermediate goal of this project to build a large database of estimates of alphabetical authorship norms over all fields of science. These estimates will capture a long time span and be subdivided for different numbers of authors. It is expected to find large heterogeneity in the principles of how authors assign credits for their contributions in different fields, some of which are name ordering based on equality (alphabetical order), effort (contribution levels) or status (principal investigators as last authors). Status norms will be identified by the status "corresponding author".

The principal investigator and his collaborator Dr. Fabian Winter has conducted preliminary analyses of the Web of Science data base. This confirms substantial heterogeneity over a selection of three disciplines (Fig. 4). This gives weight to the basic assumption that different name ordering norms exist in different disciplines and yields ground for normative conflicts about contribution credits in interdisciplinary working groups. This also demonstrates the usefulness of equation 1, since norms are robust with respect to different co-author group sizes (Fig. 4).

While the state of the art is restricted to merely counting the rate of alphabetically ordered papers in an increasingly methodologically sophisticated way, this project aims to explain name ordering norms over a larger set of fields, time spans and subdivision of co-author group sizes. This allows analyzing causes and consequences of inequalities, emergence of different team sizes and networks in different fields.

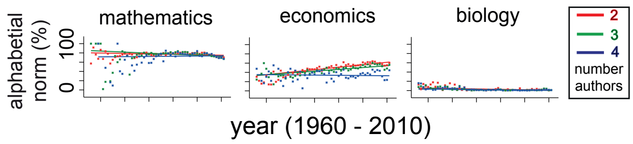

Fig 4. Trend of intentionally alphabetically ordered papers in three fields over 50 years subdivided by author group sizes. Preliminary data analysis of the Web of Science data base by Rauhut and Winter (2012).

Hypothesis A.1 (Equity trend): *Authors on publications are increasingly ordered non-alphabetically.*
It is expected that the more authors, the more difficult to split up contributions equally. Further, the larger the teams, the larger the diffusion of responsibility (Darley and Latane, 1968). If teams reach a certain size, it takes a "leader" to bring a project forward. Due to these factors, it is expected that there is a trend towards equity-based contribution norms regarding non-alphabetical name ordering.

Hypothesis A.2 (Equity advantage of large teams): *The more co-authors, the larger the citation advantage of non-alphabetical name ordering.*
It follows from the considerations above that effort-based contribution norms work more smoothly and are less prone to conflicts in large teams than equality norms of alphabetical name ordering. The less conflicts the better the results of joint work. Hence, it is to be expected that better work is also recognized more widely and consequently more often cited. In sum, non-alphabetically ordered work should have more citations than alphabetically ordered work and this equity advantage becomes larger for larger teams.

Hypothesis A.3 (Interdisciplinary normative conflicts): *The larger the differences in name ordering norms in the co-authors' disciplines, the less citations.*
Conflicts can arise from different disciplinary cultures, in which authors have been scientifically socialized. Often, social norms are taken for granted and are not explicitly stated up front. Scholars from different disciplines may have increasingly different expectations and conflicts, the larger the differences in the empirically measured name ordering norms of their disciplines. More citations are used here as proxy for valuable work and – inversely – less citations as proxy for conflicts. These comparisons should also take control variables into account, for example journal impact factors and the number of co-authors.

Hypothesis A.4 (Z-effect on working alone): *The later the position of the surname initial of scientists, the higher the probability to work alone. This effect becomes stronger, the stronger the alphabetical norm in the field (interaction effect).*

Authors with late surname initials have decreased visibility in fields with an alphabetical norm. In the case of three authors, a paper is typically abbreviated by "first-author et al." with the effect that the first author receives higher visibility. In addition, bibliographies are often alphabetically ordered with the implication that even for two authored papers, the first author receives higher visibility, because the first author is the sorting criterion and catches the eye.

The state of the art primarily investigated disadvantaged surname initials in economics over a short period of time. However, this project allows a full-fledged analysis of the implications of inequality in surnames in all academic fields over a longer period of time. This allows to test the following novel idea. Authors with later positions of surname initials in the alphabet have a higher probability to work alone. In addition, this effect becomes stronger, the stronger the alphabetical norm in the field. This interaction effect will be called the "Z-Hypothesis" (see Fig. 5). The previous studies only investigated single fields such as economics and the consequences of disadvantaged "Z-authors". However, there is no study to date testing how Z-authors react preemptively by adapting their publication strategy to working alone. The construction of the database on name-ordering norms allows estimating the hypothesized interaction over all 241 fields in the Web of Science data base. The following logistic regression model will be estimated separately for each of the 241 academic fields:

$$\log \frac{\pi(\text{single author})}{1-\pi(\text{single author})} = \alpha + \beta \cdot \text{letter}. \tag{2}$$

Here, π is the probability of being a single author of one publication of one specific author in the database. "Letter" is the standardized position of the surname initial in the alphabet with $A = 1/26, B = 2/26, \ldots, Z = 26/26$. By ordering the estimated 241 logit coefficients by the alphabetical norm in each field, it is possible to test the Z-hypothesis as sketched in Fig. 5. The increasing effect of logit coefficients for increasing alphabetical norms can be estimated using a linear (or non-linear) fit through all coefficients, weighted by the inverse of the standard error (for the inverse variance method, see e.g. Borenstein et al., 2011). An alternative model specification would be the estimation of one model over all 241 fields, adding to equation 2 an additional interaction parameter for the alphabetical norm in the field (using a multilevel model with fields as second level and publication as first level). The advantage of the suggested procedure of estimating separate models for each field yields robustness estimates, since the same model is specified 241 times and the coefficients are expected to follow the order given by the alphabetical norm in the field.

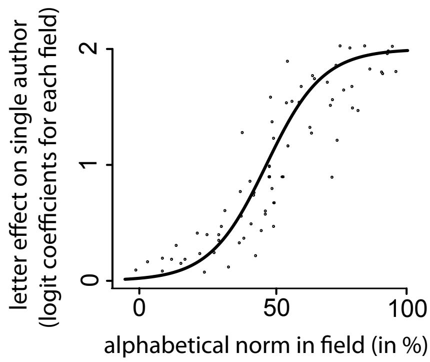

Fig 5. Conceptual representation of the Z-hypothesis (hypothetical data). Each point represents one logit regression coefficient from eq. 2 for each of the 241 fields in the Web of Science data base. Coefficients for each field (y-axis) are plotted by the alphabetical norm in the field (x-axis). The Z-hypothesis is confirmed if the letter effect increases with the alphabetical norm.

Hypothesis A.5 (Z-effect on single author citations): *The later the position of the surname initial of scientists, the more citations for single-authored work. This effect becomes stronger, the stronger the alphabetical norm in the field (interaction effect).*

The above considerations of the Z-hypothesis do not only apply to scientists' general strategy of either working alone or in teams, but also to how much effort they put into which publication. Hence, it follows from the above described logic that Z-scientists (those with late surname initials) put more effort in single-authored publications and A-scientists (those with early surname initials) put more effort in team publications. The hypothesis can be tested by using citations as proxy variable for effort.

Hypothesis A.6 (Z-effect on network size): *The later the scientist's surname initial in the alphabet, the fewer co-authors. This effect becomes stronger, the stronger the alphabetical norm in the field (interaction effect).*

The Z-Hypothesis can be extended to studying letter effects on the network degree of authors: the later the surname initial in the alphabet, the fewer co-authors. This can is tested by specifying for each of the 241 academic fields in the Web of Science data base the following negative binomial regression model

$$\mu(\text{co-authors}) = \exp(\alpha + \beta \cdot \text{letter} + \epsilon), \tag{3}$$

where μ is the mean number of co-authors, letter the standardized surname position in the alphabet and $epsilon$ the error term for overdispersion. Regression coefficients are sorted by the alphabetical norm in the field, similar to Fig. 5, however with expecting a negative linear (or non-linear) effect of β-coefficients with the alphabetical norm in the field. Here, also inverse standard errors are used as weights of regression coefficients.

Project B: Norm perception, social value orientation and enforcement of cooperation

While project A analyzes the "objective", behavioral side of publication norms by investigating publication records, this project measures the "subjective", perceptual side using survey data. An online survey will be used, sampling scientists from a large variety of disciplines. It will be started by sampling researchers at Swiss universities from social sciences, natural sciences, engineering and medicine at different points in their careers. There will be a pilot study with a target sample size of 100 participants. The full Swiss study has a targeted sample size of 1000 participants. In case some universities do not provide their address list, student assistant will collect respective Email addresses from the scientists' homepages.

The survey will be extended to European and US universities, when design and questionnaire is improved based on the analysis of the Swiss data. Selected US and European universities will be asked for their address pools. The target sample size of this study is 3000, allowing comparisons of countries, elite and non-elite universities and fields, all of which with different Ph.D. programs, academic job markets and tenure procedures.

The first aim of the project is to substantiate the findings from project A, using more detailed and fine-grained measures of publication norms in different fields and respective publication strategies of scholars. This procedure compensates for the relative weakness of both data sources. While project A uses "objective" but relatively sparse bibliographic data, project B uses "subjective" but relatively rich survey data.

One survey block covers distributive justice norms in research. This is evaluated by vignettes, using the survey design of Maciejovsky et al. (2008). Vignettes show name ordering examples of hypothetical publications. The respondents have to evaluate whether authors contributed equally or unequally to the work (Fig. 6.) Vignettes vary in alphabetical order and number of authors. In the case of an unequal evaluation of contributions, respondents have to rate the relative contributions of the authors in percentages. This allows to estimate whether respondents adhere to an equity or equality norm. In this way, the planned survey will measure the extent to which co-authors from different fields have different opinions about how much a first, second, third or forth author should have contributed to a paper. It also allows to make inferences on the conflict potential of scientists from different disciplines. In addition to using vignettes, there will be item batteries asking for adherence to equity and equality norms more in general. This item battery focuses on attitudes towards sharing work load, competition in work compensation, performance-oriented salaries and redistribution policies in universities and research teams.

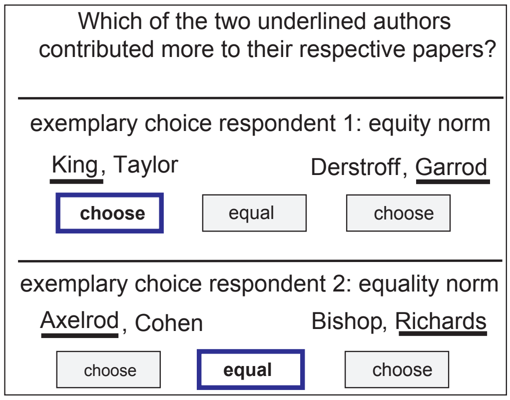

Fig 6. Survey measure of scientists' adherence to equity (non-alphabetical) or equality (alphabetical) norm. Vignette example 1 shows two separate, two-authored fictitious publications (King & Taylor vs. Derstroff & Garrod). The respondent is asked to make inferences from name order to relative contributions (design follows Maciejovsky et al. (2008)).

Hypothesis B.1 (Equality illusion): *The smaller the average number of co-authors and the smaller the observed rate of alphabetically ordered papers in a field, the larger the equality illusion, i.e. the larger scientists' overestimates of alphabetical name ordering.*

A related crucial question is why the equality norm of ordering authors alphabetically persists so long in many fields such as economics, while equal contributions of co-authors are, in fact, very rare. As Lake (2010, p. 2) notes, "alphabetical listings of authors are uninformative and, in practice, unfair. . . . Economists 'know better' than to allocate professional rewards to those whose surname happen to begin with letters early in the alphabet, but they do so anyways."

One reason of the persisting equality norm in assigning contribution credits may be a cognitive illusion. This novel idea, based on three assumptions, has not yet been empirically explored. First, alphabetically ordered publications with few co-authors are likely to be unintended and incidental. This probability is for two authors 50 %, for three authors 17 % and declines by $\frac{1}{n!}$ (see Fig. 3 and equation 1). Second, it is likely that there is a correlation between the average number of co-authors and the alphabetical norm in a field (see Waltman, 2012). Third, this relationship seems to be driven by incidentally alphabetical authorships.

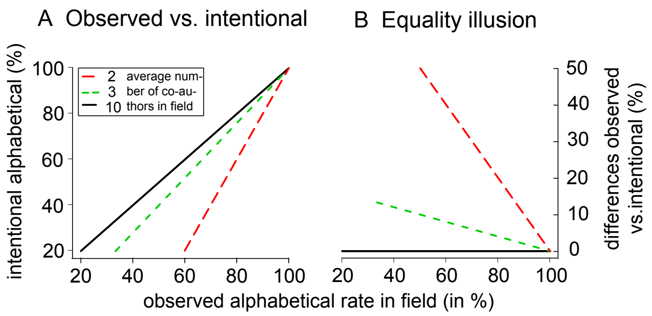

Fig 7. Equality illusion for 2, 3 and 10 average co-authors (based on eq. 1). Panel A shows differences between observed and intentionally alphabetically ordered papers by 2, 3, and 10 average co-authors in a field. Panel B displays the differences between observed and intentional alphabetical order (i.e. "equality illusion").

Conclusively, there is a large difference between the observed and the intended rate of alphabetically ordered articles in fields with low numbers of co-authors. Using correction formula 1, the differences between observed and intentionally alphabetically ordered articles can be specified for different averages of co-authors in respective fields. Figure 7A illustrates the analytical relationship between observed and incidental alphabetical authorship for different average numbers of co-authors in a field. For example, in fields with typically two co-authors on multi-authored papers, an observed rate of 60 % alphabetically ordered articles only corresponds to 20 % intentionally alphabetical papers (see red line in Fig. 7A). This means that even when most scientists do not adhere to the equality norm it may seem that they do.

Hypothesis B.2 (Formal enforcement of cooperation in team disciplines): *The larger the median number of co-authors in a field, the more formal enforcement of cooperation.*

A questionnaire battery is developed which measures the knowledge, acceptance and application of informal and formal procedures of enforcing cooperation among uncooperative collaborators. Informal punishment consists of ending uncooperative relationships, spreading rumors about uncooperative collaborators, or confronting collaborators with complaints. Formal punishment consists of written agreements, i.e. “prenuptials” about sharing work load, authorship and data. In addition, questions about formal punishment will ask whether the ombudsman or other university representatives have been consulted in case of conflicts. It is hypothesized that larger teams require more formal punishment techniques than smaller teams.

Hypothesis B.3 (Prosocial scientists in team disciplines): *The larger the research teams, the stronger the scientists' prosocial value orientation. These disciplinary differences become larger, the higher the scientists' career status (interaction effect).*

The questionnaire contains a novel, sensitive and high-resolution measure of social value orientation, called the SVO slider measure (Murphy et al., 2011). The measure has six main items, asking for divisions of joint money between the respondent and another participant in the survey. Technically speaking, these monetary allocation decisions are dictator games. The variation of different decision schemes allows the computation of SVO scores and types (Fig. 8). These types consider respondents who maximize other's payoffs (altruistic), joint payoffs (prosocial), own payoffs (individualistic), or differences between own and others' payoffs (competitive). The sovial value orientation score is calculated by the angle in the self-other allocation plane, starting from the center of the circle (Fig. 8). Perfect altruists are represented by an angle of $61°$, prosocials by $45°$, individualists by $0°$ and competitive ones by $-16°$. This score can be used as metric predictor in regression models.

Both monetary payoff decisions will be implemented so that in every game, one of the six decisions is randomly taken as payoff-relevant. Participants can choose whether to be paid by vouchers (e.g. for purchases at “Amazon”), by mail (postal banknotes and stamps) or by cash transfers (Rauhut and Rössel, 2013). A lottery will be used selecting every fifth out of one hundred participants for monetary payments. Previous SVO experiments yielded payments of 82 Euros per subject (Murphy et al., 2011), yielding estimates for total payments by the lottery discounts (i.e. multiplied by $\frac{5}{100}$).

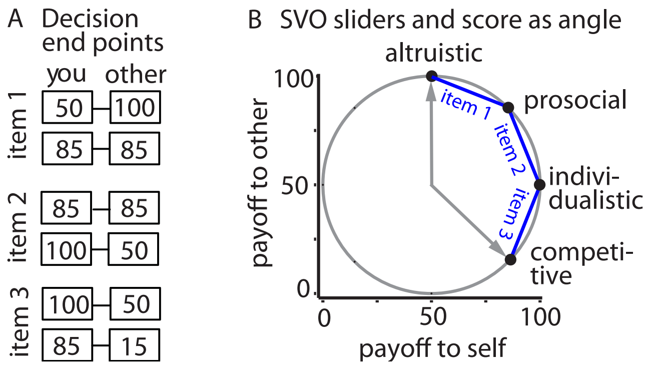

Fig 8. Simplified, 3-item representation of the social value orientation slider measure (SVO) of Murphy et al. (2011).(A) Monetary payoff allocation between two respondents. Item 1 asks for tradeoffs between altruistic and prosocial, item 2 between prosocial and individualistic, item 3 between individualistic and competitive payoff allocations. (B) Self-other allocation plane, where divisions “slide” between pure types (blue lines).

The measures for team size are elicited in two ways. The disciplinary distinctions (“solo” vs. “team” disciplines) are measured by the average number of co-authors from the Web of Science data base. The team size of the surveyed researcher is also elicited in the survey, yielding another measure for team size. It is expected that there are more researchers with a prosocial value orientation in disciplines with large teams and in those with small teams more researchers with an individualistic orientation. In these disciplines, it is important to develop one's own theory and point of view and to write single-authored papers instead of promoting team work and cohesiveness.

Project C: Team effects on publishing biased and faked results

This project will analyze cooperation failures and violations of scientific norms in research groups. Norm violations in science can have different magnitudes ranging from biased publication strategies to faking data. It is plausible that scientific misconduct is related to the size of the working group. However, the effects of team size on norm violations can go in either way.

Hypothesis C.1 (Social control): *The larger the team, the less norm violations.*

There is more social control in larger co-author groups (Auspurg and Hinz, 2011). Compared to working alone, other scientists receive insider knowledge in the data collection and production process of an article. The more co-authors, the higher the probability that one of them has a skeptical attitude and demands receiving in-depth information on the production process of critical results. Hence, the more co-authors, the less scientific misconduct (*control hypothesis*).

Hypothesis C.2 (Volunteering): *The larger the team, the more norm violations.*

There is more diffusion of responsibility in larger co-author groups. The more authors, the higher the probability that all involved authors think that the others closely checked data collection or processed results, while in fact, nobody did it. The fact that the probability of volunteering decreases with increasing group size is well known by "diffusion of responsibility" (Darley and Latane, 1968) and the "volunteer's dilemma" (Diekmann, 1985). Applied to scientific collaboration, we would expect that with more co-authors there would be more scientific misconduct (*volunteer hypothesis*). While there are empirical corroborations in abstract cooperation problems (Franzen, 1999)there is no study to date testing the implications of the volunteer's dilemma for scientific misconduct.

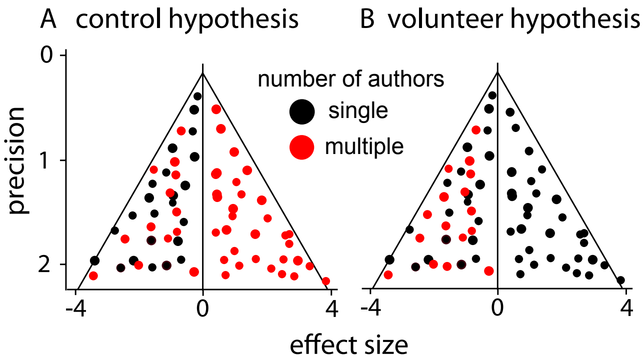

Fig 9. Schematic funnel plots of standardized effects against precision (hypothetical data). Panel A shows the control hypothesis, where larger author groups have less publication bias. The funnel of single-authored publications (black dots) is left-skewed, the multi-authored one (red dots), symmetric. Panel B illustrates the volunteer's hypothesis, where larger co-author groups show more publication bias with the reversed pattern, i.e. for single symmetric and for multi-authored, left-skewed.

The research design of this project will utilize meta-analytic methods from statistics and computer science to detect scientific misconduct. The first kind of misconduct is the so-called "publication bias". The publication bias is defined as a biased selection of published results in favor of the research hypothesis. This can be explored by so-called funnel plots, which were introduced by Light and Pillemer (1984) and discussed for the social sciences by Weiss and Wagner (2011). The method requires to collect a large sample of reported test statistics from journal articles in order to plot effect estimates at the horizontal axis against precision of tests at the vertical axis. Effect sizes are often measured by log odds ratios and precision by standard errors (see Sterne and Egger, 2001, for a discussion of different methods). Because precision increases with sample size, small studies scatter widely around the mean standardized effect and large studies narrowly. If there is no publication bias, the plot resembles an inverted funnel. If there is bias, the funnel is asymmetric and skewed, because confirming studies have a higher likelihood to be published.

Funnel plot asymmetry can be used to explore whether the control hypothesis or the volunteer hypothesis is true. Studies have to be subdivided by the number of co-authors; in the most simple version, single-authored studies are compared with multi-authored ones (see Figure 9). If the control hypothesis is true, there is more publication bias in single-authored publications and the funnel plot of single authors is asymmetric and for multi-authored, symmetric (Fig 9A). This pattern would be reversed if the volunteer hypothesis is true (Fig 9B). Also other tests of publication bias will be used, e.g. the Caliper test (Gerber and Malhotra, 2008; Auspurg and Hinz, 2011).

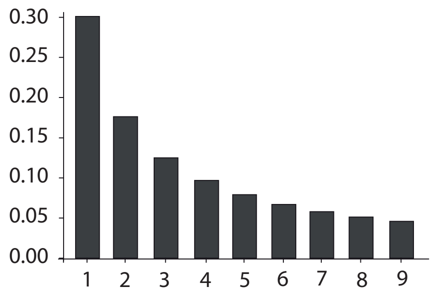

Fig 10. Benford distribution of first digits (adapted from Tödter, 2009). Comparison between empirical distributions of first digits of published regression coefficients with Benford yields inferences about fake data.

More serious scientific misconduct is publication of fake data. It is possible to make inferences from published test statistics to the probability of faked data in a field, using many coefficients from many articles. One version of this "data mining" approach is testing whether published regression coefficients follow the Benford (1938) distribution (Fig. 10). This idea exploits the fact that digits do not occur with equal frequency. The probability that "1" is the first digit is not 11 % , as under a uniform distribution, but it is 30 %. When inventing and faking data, scholars are often not aware of the skewed distribution of digits (Tödter, 2009; Diekmann, 2010).

There are, however, few studies which use discrepancies from the Benford distribution to explain misconduct by structural variables such as team size. In this part of the project, Benford tests for single and multi-authored papers will be compared to test the influence of the number of authors on publishing fake data. One approach is to compare the distribution of first digits of regression coefficients against the theoretical distribution. This test strategy allows an empirical corrobation of the control against the volunteer hypothesis.

In addition to analyzing reported test statistics, questions about scientific misconduct will be included in the above-mentioned survey of scientists (project B). This covers direct questions about biased publishing behavior and more severe forms of producing fraudulent data and plagiarism. Modern methods to reduce social desirability bias for these sensitive behaviors will be used, such as the randomized response (Warner, 1965; Tourangeau and Yan, 2007) or the item count method (Jann et al., 2012).

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