SCIENCE, TECHNOLOGY & INNOVATION INDICATORS

Open indicators: innovation, participation and actor-based STI indicators
PARIS 2017

Influence of cognitive distance on grant decisions[1]

Peter van den Besselaar[*], Ulf Sandström[**]

[*]p.a.a.vanden.besselaar@vu.nl
Vrije Universiteit Amsterdam, Network Institute & Institute for Societal Resilience, De Boelelaan 1081, 1081 HV, Amsterdam (Netherlands)

[**]ulf.sandstrom@indek.kth.se
KTH Royal Institute of Technology, Indek ITM, SE-10044, Stockholm (Sweden)

ABSTRACT
The selection of grant applications generally is based on peer and panel review, but as shown in many studies, the outcome of this process does not only depend on the scientific merit or excellence, but also on social factors, and on the way the decision-making process is organized. A major criticism on the peer review process is that it is inherently conservative, with panel members inclined to select applications that are line with their own theoretical perspective. In this paper we define 'cognitive distance' and operationalize it. We apply the concept, and investigate whether it influences the probability to get funded.

INTRODUCTION
Core in any grant selection procedure is the review panel, evaluating, discussing and selecting a small percentage of the applications for funding. Peer review plays an important role, but as shown in many studies, the outcome of this process does not only depend on the scientific merit or excellence, but also on social factors (e.g., Sandström & Hällsten 2008; Lamont 2012; 2014) and on the way the decision-making process is organized (e.g., Van Arensbergen 2014; Langfeldt 2004). Importantly, this may lead to biased outcomes as has been empirically shown in quite some studies since the 1970s (Cole 1994; Chubin & Hackett 199; Wennerås & Wold 1997).

One of the core problems with peer review is that the reviewers are often not the real peers, as they have to cover a much wider domain than only what belongs to their real expertise (Sandström 2009; Wang & Sandström 2015). This may result in a conservative approach, where panel members select applications that are in the mainstream of their field, or (even more narrowly) are related to their own work (Travis & Collins 1991). This kind of 'cognitive bias'[2] may be unavoidable due to the "cognitive structure of science" which is characterized by "the existence of cognitive boundaries within and between scientific specialties and disciplines" (Travis & Collins 1991). But if panel members not really represent the top of the field (Sandström 2012), the risk of conservatism may be even larger.

[1] This work was supported by JR and EC. The authors thank Charlie Mom and Lucia Polo Alvarez for support in the data collection and for comments on earlier versions. The paper is based on the GendERC project, funded by the ERC (grant 123456).
[2] The basic idea about cognitive bias and the way to measure is can be found in Sandström (2009).

Cognitive distance as an analytical variable

Cognitive distance refers to the general "homophily mechanism" in social network theory: more similar nodes are more likely to be connected than less similar nodes (Monge & Contractor 2003). Travis & Collins indicates a sentiment among researchers to guard their own subject area implicating that money going to the own area is good spent money. Cognitive distance between two units can be defined as the level of similarity between the research contributions done by them. If two researchers are in the same specialty (or specialties), the cognitive distance is low. If they do not share any research specialty, the distance between the researchers is large. We deploy a strategy that is based on hybrid methods for identifying research topics, an approach that emerged in the mid-2000s (Van den Besselaar & Heimeriks 2006; Liu et al. 2010). Within this hybrid approach, similarity between papers is defined in terms of title words used (measuring the topic covered), and in terms of the references used (measuring the theoretical tradition of the paper). The advantages of combining these two approaches are evident (Van den Besselaar & Heimeriks 1996; Boyack & Klavans 2010. Cognitive distance between two authors can be calculated by aggregating the distances between the papers that were authored by the two authors. Here we use the approach developed in (Qi & Sandström 2015)[3], supported by the BMX infrastructure to calculate the bibliometric indicators (Sandström & Sandström 2009; Sandström 2014).

Research questions

We investigate the relation between applicants' success rates and cognitive distance. As success should depend on performance, we take indicators for past performance of the applicant into consideration. Specifically, we therefore test the following hypotheses:

(i) Applicants with a smaller average distance to the panel members have a higher chance to be funded than applicants in topics/ topical clusters without panel members.

(ii) The previous patterns remain exist when controlling for performance level.

DATA AND METHOD

For analysing the cognitive distance, we use data on the publications of the panel members and of the applicants since 2006. For the latter, this covers the eight years period after the PhD, the maximum allowed for applicants. Panel members have a much longer publication history. But we expect that the more recent work is the most relevant in the context of our research question. We calculate the distance to (or: similarity between) an applicant and each of the panel members. We derive from those two indicators for cognitive distance: (i) the first indicator is the average of these distances between applicant A and all panel members Pi. (ii) As a second indicator we use the cognitive distance to (or similarity with) the nearest panel member. Both are needed as an applicant may be close to some and further away from other panel members, whereas another applicant may have about similar moderate distances to the panel members. By including both distance indicators, we capture both situations.

We use here data of four panels that together include about 40 panel members and 400 applicants. For each of these panel members and applicants we downloaded from WoS all publications since 2006. We checked these publications against CVs and where needed homepages. The data collection was very time consuming, mainly because of the need to identify publications and disambiguate the names of the panel members and applicants. The data were collected and double checked several times. Therefore the quality of the dataset can be considered as highly consistent and reliable.

[3] For a a detailed description of the method: (Sandström 2009; Qi & Sandström (2015); Sriwannavit & Sandström (2015).

Using these publication data, we could calculate at *the panel level* the cognitive distance measure between all involved – the applicants and the panel members.
The *cognitive distance* between two authors is defined as the reciprocal of the "hybrid similarity" (see Glänzel and Thijs, 2011) between the set of papers published by each author (included in the publication data), using 1) "bibliographic coupling" and 2) "title similarity" as similarity measures.

The *bibliographic coupling* between two authors is a cosine normalized (see Salton & McGill, 1983) measure of the rate of shared cited references, defined below where a_i and b_i is the occurrences of (number of) cited reference *i* in the publication set of author *a* and *b*, respectively, and *N* is the total number of unique cited reference in the publication set.
The *title similarity* is calculated using Latent Dirichlet Allocation method (LDA) (Blei et al. 2003), which creates a distribution of "topics" over papers (see Blei et al. 2003). The title similarity between two papers is a cosine normalized measure of the rate of shared topics, defined in the same way as in the formula above except that the co-occurrences are shared topics instead of shared cited references.

$$sim(a,b) = \frac{\sum_{i=1}^{N} x_i\, y_i}{\sqrt{\sum_{i=1}^{N} x_i^2}\sqrt{\sum_{i=1}^{N} y_i^2}}, \qquad x_i = \frac{a_i}{\sqrt{\sum_{j=1}^{N} a_j^2}}, \qquad y_i = \frac{b_i}{\sqrt{\sum_{j=1}^{N} b_j^2}}$$

The bibliographic coupling and the title similarity is combined using the *hybrid similarity* approach suggested by Glänzel and Thijs (2011), where η is the bibliographic coupling and $\xi$is the title similarity; λ has been set to 0.833. The cognitive distance is the reciprocal of the hybrid similarity, i.e. 1/*r*.

$$r = \cos(\lambda \cdot \arccos(\eta) + (1-\lambda) \cdot \arccos(\xi)), \qquad \lambda \in [0,1]$$

Clustering procedures uses the SLM (Smart Local Moving) algorithm suggested by Waltman & van Eck (2013). Resolution was set to 1.5 for all panels. This leads to networks of panellists and applicants in which all nodes are connected with all others, as there is always some (very low) similarity. We have for each of the applicants the cognitive distance to all panel members in the panel. We now can calculate the average cognitive distance between an applicant and all panel members, as well as the distance the applicant has to the nearest panel member (or members). In principle, similarity is between 0 (completely dissimilar) to 1 (completely similar). But in our panels, the minimum and maximum values are 0.001 and 0.31. respectively.

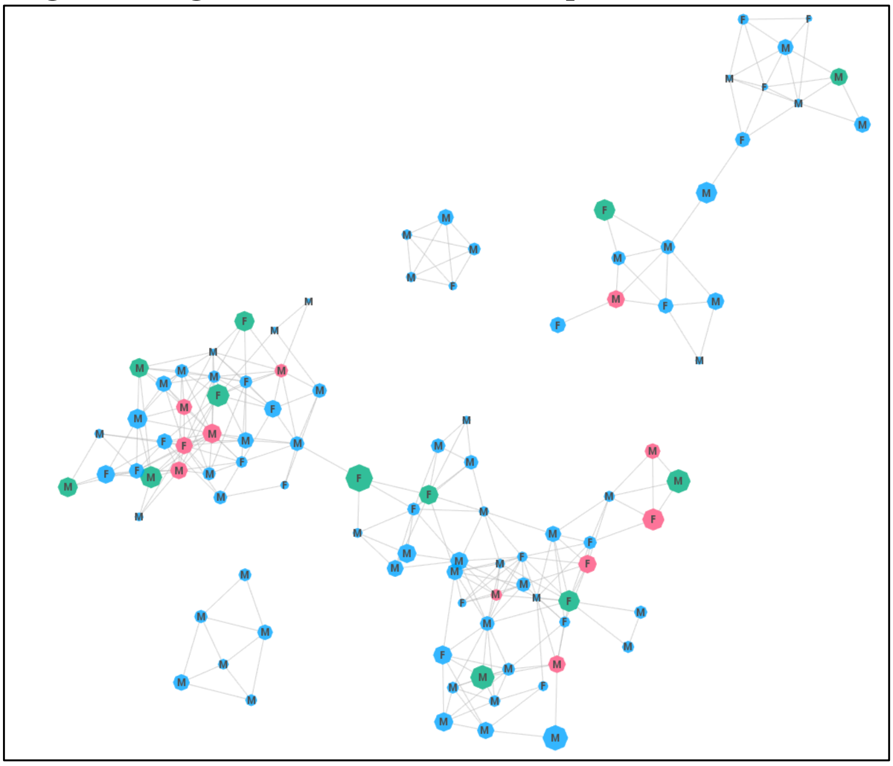
Cognitive distance is not the only relevant particularistic (Merton 1973, Cole 1992) factor that may influence decision-making. One may also take into account other distance measures, such as geographic, organizational, cultural (language, nationality, gender) distance, and a variety of personal relations (co-authors, whether the applicants previous supervisor is a friend, colleague, co-author of one or more panel members, and so on).
For analysing the effect of cognitive distance on the panel decision, one needs to take the meritocratic dimension into account: the quality of the PI. Using the publications of panel members and PIs, we calculate the following performance indicators:

- NCSf: the field (subject categories of the WoS) Normalized Citation Score; publications period = 2006-2012; normalization includes document categories and publication year; citations: open citation window until 2014.
- TOP5: Share of the papers of an author by that are in the top 5% most cited papers, taking

fields (subject categories), document categories and publication year into account during the period 2006-2012.

- FAP: Field Adjusted Production during the period 2008-2012. Different fields have different productivity levels (Sandström & Sandström 2009; Sandström & Wold 2015), and normalization (here based on Nordic reference values) is needed for comparing applicants.
- PM Model: We multiply (fractionalized and FAP normalized) publications within each percentile group (1%, 5%, 10%, 25%, 50% and 100%) with percentile group dependent credits: 100, 20, 10, 5, 2, and 1 credit respectively (for an explanation: Sandström & Wold 2015).
- PM Level: We use the complete population of 50,000 Swedish researchers during 2008-2012 as a benchmark: we calculate the PM model score for every applicant, and determine in which Swedish percentile the applicant. That gives the value of the indicator PM Level. As Sweden is a well-performing science country, this is a reliable approach. In this way it can be assessed whether a PI in the recent period belongs to the top 1% researchers, the top 5%, and so on.

Figure 1: Cognitive distance network of panel A



Open Ord edge cut 0.8, Kamada-Kawai layout
Blue: nodes unsuccessful applicants; red= successful applicants; green = panel members;
M= male panel member/applicant; F= female panel member/applicant
Size = performance level

FINDINGS

In Figure 1 we show the proximity network of one of the panels. The distance between nodes on the map indicate cognitive distance: the closer two nodes are, the more similar. The size of the nodes reflects their performance level. The map is based on an edge cut using Open Ord algorithm (Martin et al. (2012) and the Kamada-Kawai layout algorithm (Kamada & Kawai 1989). Several unconnected components are visible, suggesting that the panel covers a heterogeneous field. The components without panel members may indicate the emergence of new topics. Visual inspection of the figure shows that generally the funded applicants (red nodes) are not too far from the panel members (green nodes) in the left and the right of the map. In contrast, quite some unsuccessful applicants (blue nodes) are far from green nodes (e.g. the component in the right top) and sometimes even in separate components (which means a very low degree of similarity). But we also see green nodes with only blue nodes in the vicinity (centre of the map, and the top right). There we find panel members but no granted applicants – so it is no guarantee that close distance leads to grants. As the size of the nodes reflects their performance level the size distribution of red and blue applicants indicates that not always the most performing applicants are granted.

The table 1 gives an overview of the findings. For each of the four panels we give show whether successful applicants are more similar to the panellist than the non-successful. The results are the same for the distance to the nearest panel member as for the mean distance to all panel members. We summarize the five performance scores into one. We compare the performance of the successful with the performance of the panellists, and with the best non-successful. Obviously, in three (A, B, D), cognitive similarity has a positive effect on the probability of getting a grant. And – comparing the successful with the non-successful applicants) this is not explained by performance differences. Panel C is deviant: cognitive similarity has a negative effect in panel C, and at the same time, performance does not seem to have an impact on being selected.

Table 1: Overview results

	panel A	panel B	panel C	panel D
Successful more cognitive similar to panel?	More similar	More similar	Less similar	More similar
N granted perform better than				
- All non-granted applicants	Yes	Yes	Equal	Yes
- N best non-granted applicants	Equal	Equal	No	No
- 2N best non-granted applicants	No	Equal	No	No
Panellists better than applicants	Yes	Yes	Yes	Yes

CONCLUSIONS

We found that cognitive distance seems to play a role in grant decision-making. Three interpretations come up. (i) As grantees outperform non-grantee, which explains why they are selected. As table 1 shows, this is not overall the case. (ii) Panel members are selected as they are top researchers, representing the most important research fronts in their fields. Therefore, it should be expected that well performing applicants who are more similar to panellists do have a better chance to be funded, as they and not the others, are in the active research fronts. (ii) Panellists are generally older, and although they may be top researchers, they represent yesterdays' research fronts. The cognitive distance effect may in that case lead to a conservative decision making, and any promising new developments can be missed. In practice, it may be somewhere in between. Further research, however, is needed as distribution of research grants may directly influence the research field (and indirectly through the effects of grants on the careers of the applicants).

Further research could focus on:

- Including more panels, as that would make the comparison more robust, and would also enable (multi-level) statistical analysis.
- Using topic maps and positioning of panel members and applicants on those topic maps as an alternative approach to cognitive distance.
- Extending the analysis to other networks than only cognitive networks: networks based on nationality, language, shared work environments, informal relations, gender.

- As generally a few panel members review an applicant, we may apply cognitive distance to the relation with those panel members only.

REFERENCES

Blei, D.M., Ng, A.Y. and Jordan, M.I. (2003) Latent Dirichlet Allocation. *Journal of machine learning research* **3**, 993-1022.

Bornmann, L. (2008), Scientific Peer Review. An Analysis of the Peer Review Process from the Perspective of Sociology of Science Theories", Human Architecture: Journal of the Sociology of Self-Knowledge **6**, 2, 23–38

Boyack KW & R Klavans (2010). Co-citation analysis, bibliographic coupling and direct citations: which citation approach represents the research front most accurately? *JASIST* **61**, 12, 2398-2404

Chubin DE & Hackett, EJ (1990). *Peerless science: peer review and U.S. science policy*. SUNY Press.

Cole S (1992). *Making science: between nature and society*. Cambridge, Mass.: Harvard University Press.

Glänzel W & B Thijs (2012). Using 'core documents' for detecting and labelling new emerging topics. *Scientometrics* **91,** 2

Jayasinghe, U.W., Marsh, H.W. & Bond, N. (2003), A multilevel cross-classified modelling approach to peer review of grant proposals. The effects of assessor and researcher attributes on assessor ratings, *Journal of the Royal Statistical Society: Series A (Statistics in Society)* **166**, 3, 279–300.

Kamada T & S Kawai (1989). An algorithm for drawing general undirected graphs. *Information Processing Letters* **31**, 1, 7–15

Lamont M. 2012. Toward a Comparative Sociology of Valuation and Evaluation. *Annual Review of Sociology* **38**, 21, 201-221

Liu XH, S Yu, F Janssens, W Glänzel, Y Moreau & B de Moor (2010). Weighted Hybrid Clustering by Combining Text Mining and Bibliometrics on a Large-Scale Journal Database. *JASIST* **61**, 6

Martin S, WM Brown, R Klavans, and K Boyack (2012). OpenOrd: An Open-Source Toolbox for Large Graph Layout. *SPIE Conference on Visualization and Data Analysis (VDA).*

Merton R (1973). The normative structure of science. In: R. Merton, *The sociology of science*, University of Chicago Press, pp276-278.

Monge P & N Contractor (2003). *Theories of communication networks*. Oxford University Press

Qi W & U Sandström (2015). Defining the Role of Cognitive Distance in the Peer Review Process with an Explorative Study of a Grant Scheme in Infection Biology. *Research Evaluation* **24**, 3

Salton G, & MJ McGill (1983). *Introduction to modern information retrieval*. McGraw-Hill.

Sandström U & A Wold (2015). Centres of Excellence: reward for gender or top-level research, *Thinking Ahead: Research, Funding and the Future. RJ Yearbook 2015/16*. Stockholm: Riksbankens Jubileumsfond and Makadam.

Sandström U & E Sandström (2009). The field factor: towards a metric for academic institutions. *Research Evaluation* **18**, 3, 243–250.

Sandström U & M Hällsten (2008) Persistent nepotism in peer-review. *Scientometrics* **74**, 2, 175-89.

Sandström U (2009b) Cognitive bias in peer review: A new approach. *Proceedings of 12th ISSI Conference*, Rio de Janeiro, Brazil

Sandström U (2014) *Bibliometric evaluation of SEPA-funded large research programs 2003–2013 Swedish Environmental Protection Agency. Report 6636*

Sandström, U (2012). *Granskning av granskarna: VR:s beredningsgrupper. Forskning om forskning 2/2012* [www.forskningspolitik.se]

Travis GDL & Collins HM (1991). New light on old boys: cognitive and institutional particularism in the peer review system. *Science, technology & Human Values* **16**, 3, 322–341.

Van den Besselaar P, Heimeriks G (2006). Mapping research topics using word-reference co-occurrences: a method and an exploratory case study. *Scientometrics* **68**, 377-393

Waltman, L., & Van Eck, N.J. (2013). A smart local moving algorithm for large-scale modularity-based community detection. *European Physical Journal B* **86**, 11, 471

Wennerås, C. & Wold, A. (1997). Nepotism and sexism in peer review. *Nature* **387** (6631), 341-343.