Supplementary Information for: Interdisciplinary researchers attain better long-term funding performance

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1 Supplementary Note 1: Basic information for seven research councils

This study refers to the data of research grants from seven national discipline-based research councils, which cover almost the full spectrum of research subjects in UK:

1. Arts and Humanities Research Council (AHRC) funds independent research across a wide-range of Arts and Humanities subjects;
2. Biotechnology and Biological Sciences Research Council (BBSRC) funds research in plants, microbes, animals, tools and technology underpinning biological research;
3. Economic and Social Research Council (ESRC) funds research and training on social and economic issues;
4. Engineering and Physical Sciences Research Council (EPSRC) funds research and training in engineering and the physical sciences;
5. Medical Research Council (MRC) supports research across the biomedical spectrum;
6. Natural Environment Research Council (NERC) funds research, survey, training and knowledge transfer in the environmental sciences;
7. Science and Technology Facilities Council (SFTC) operates large scale science and engineering research facilities, and funds research mainly in astronomy, particle physics, space science and nuclear physics.

Supplementary Table 1 summarizes the basic information for each research council, including the number of awarded research grants, the total funded value, the number of investigators and institutions involved, and the number of research subjects. EPSRC is the largest funding body that provides the largest number and amount of research funding, while the smallest research funder is AHRC, providing less than one-tenth of EPSRC's funding. In addition, EPSRC, MRC and ESRC are the top three research councils that involve the largest number of investigators.

2 Supplementary Note 2: Randomised null-model for co-activities between research councils

To explore the non-trivial relation between research councils, we construct the co-activity networks of investigators in Fig. 1e,f, where nodes indicate research councils and two councils are connected if they have supported the same investigator. The weights of links capture the significance of overlap between councils, quantified by the observed co-activities compared with those expected in a randomized null model [1]. Specifically, if we consider a group of N investigators, along with two research councils α and β with N_α and N_β investigators, respectively. We define the number of observed investigators who have obtained grants from both councils as $O_{\alpha\beta}$, and the expected number as $N_{\alpha\beta} = (N_\alpha N_\beta / N)$, thus the weights of link between council α and β are calculated as $W_{\alpha\beta} = O_{\alpha\beta}/N_{\alpha\beta}$, corresponding to the extent to which the observed investigators exceeds the random expectation. In this way, the link weights in the network are not influenced by the sizes of research councils at either ends. We find that all the presented link weights between councils have $W < 1$ in both periods, indicating that generally the connections between councils are not significantly higher than expected, and the overlaps between the remits of councils are relatively limited.

3 Supplementary Note 3: Basic features of research institutions

To examine the characteristics of institutions, we quantify the institution size by the total number of distinct investigators who have obtained at least one research grant under the institution, and institution ranking by the total amount of research grants awarded to an institution between 2006 and 2018. Institutions with less than 5 funded research projects during the above period have been excluded, and there are a total of 199 considered research institutions. We find that the number of investigators is very heterogeneously distributed among institutions (Supplementary Figure 2a), with elite institutions having a higher number of funded investigators and most other institutions having very few funded investigators. Supplementary Figure 2b reveals that the average number of research grants received per investigator is negatively correlated with one's institutional ranking. Supplementary Figure 2c further illustrates that there is a negative correlation between the institutional ranking and the fraction of cross-council investigators, indicating that the investigators in elite institutions are more likely to secure funding from different research councils. This is probably because the leading institutions have stronger capacity to conduct research across various scientific domains.

By fitting a power-law model to the empirical binned data of institution size [2], we find that most institution sizes are small, with only a few elite institutions with a high reputation having a large number of funded researchers (Supplementary Figure 2d). Also, both the average number of grants obtained by each investigator and the fraction of cross-council investigators positively correlate with the size of their affiliations (Supplementary Figure 2e-f), indicating that the investigators in large institutions averagely have obtained more research grants, and have more opportunities and resources to secure funding from different research councils.

4 Supplementary Note 4: Robustness check for different window lengths and institution stratification

To ensure that our results are not affected by the selection of time window length, we here consider two 5-y compared period and repeat all our analysis. For the two tiers of institutions (Supplementary Figure 3), we find that the institutions in Tier I have higher proportion of cross-council investigators than that in Tier II in both 5-y time windows (Supplementary Figure 4), suggesting that the investigators in top institutions are generally more likely to secure research funding from different research councils. On the other hand, it is shown that Tier II institutions have a relatively higher growth rate in the fraction of cross-council investigators (with an increase from 24% to 28%), which is four times greater than that in Tier I institutions (from 32% to 33%).

Moreover, to test if the results would be affected by the approach of institution stratification, we also try to classify the institutions into two groups based on whether they belong to the Russell Group. In total, the Russell Group includes 24 top universities in the UK, all of which have a strong reputation for academic achievement. We can see that in both two 3-y periods, the proportions of cross-council investigators in Russell Group are relatively higher than that in the group of other institutions (Supplementary Figure 5). Similarly, we also find that the group of other institutions exhibits a higher growth rate, by a factor of 28.6%, while the Russell Group represents a lower growth rate, with an increase of 14.8%.

We further check the complete temporal evolution of cross-council fraction as a function of non-overlap time windows for both tiers in Supplementary Figure 6a. One can see that the fraction of cross-council investigators in Tier II shows a higher increase from 18% to 25%, which is more than three times of the top tier (with an increase from 27% to 29%). Similar results have been observed when we have grouped the institutions into Russell universities and other institutions (Supplementary Figure 6b).

5 Supplementary Note 5: Evolution of collaboration networks and consistent structural advantage for cross-council investigators

To examine the evolution of the collaboration network, we use a sliding window of five years within which we aggregate all the partnerships occurring in the research projects. Starting in 2006, we shift the sliding the window in one-year increments, and obtain a total of 9 time slices between 2006 and 2018. We find that the normalized size of the largest connected component (LCC) increased steadily with time (Supplementary Figure 7a), reflecting better interconnectivity among different local scientific communities in the funding landscape. Note that the normalized size of LCC is obtained by dividing the size of the LCC by the total number of nodes. Moreover, the number of links in the collaboration network of each time slice grows much faster than the number of nodes (Supplementary Figure 7b). The average degree of collaboration networks shows a significant increase over periods, indicating that the investigators tend to build a much broader collaboration (Supplementary Figure 7c).

Furthermore, we check whether the structural advantage of cross-council investigators exists in different time windows. We construct a collaboration network and examine the network using two 5-y time windows, namely the first 5-y window (2006-2010) and the last 5-y window (2014-2018), respectively. There are 69% of the investigators connected in the LCC in 2006-2010, and 78% of that in 2014-2018. Through the network analysis in the LCCs, we calculate four node-level metrics, namely, degree centrality, closeness centrality, betweenness centrality and normalized effective size (see Methods). The definitions of three representative centrality measures are characterised as follows:

(i) *Degree centrality*. The normalized degree [3] centrality of node i is defined as:

$$dc_i = \frac{k_i}{N-1} \tag{1}$$

where k_i is the degree (number of links) of node i. The degree centrality values are normalized by dividing by the maximum possible degree $N-1$ in the LCC where N is the total number of nodes in LCC.

(ii) *Closeness centrality.* The closeness centrality [3] of a node i is defined as the reciprocal of the average shortest path distance to i over all $N-1$ reachable nodes in the LCC:

$$c_i = \frac{N-1}{\sum_{j=1}^{N-1} d(i,j)} \tag{2}$$

where $d(i,j)$ is the shortest-path distance between i and i, and $N-1$ is the number of nodes that can reach i. Closeness centrality of a node reflects the overall distance between that node and the rest of the nodes in the network.

(iii) *Betweenness centrality.* The betweenness centrality [3] of node i is defined as follows:

$$b_i = \frac{2}{(N-1)(N-2)} \sum_{a,b \in V} \frac{n_{a,b}(i)}{n_{a,b}} \tag{3}$$

where V is the set of nodes in LCC, $n_{a,b}$ is the total number of shortest paths between nodes a and b, and $n_{a,b}(i)$ is the number of shortest paths between a and b that actually go through i. If $a = b$,$n_{a,b} = 1$, and if $i \in \{a,b\}, n_{a,b}(i) = 0$.

We then quantitatively compare the structural position difference between the cross-council and within-council investigators in terms of these four metrics. In general, we find that, in both two compared periods, cross-council investigators consistently outperform the within-council investigators in terms of network centrality and brokerage power, where the conclusions remain the same as in the main text (Supplementary Figure 8 and Supplementary Figure 9).

6 Supplementary Note 6: Quantifying PIs' funding performance and outcomes

6.1 Grant-related features and their adjustments across councils and years

In this section, we enumerate the six attributes of research grants that are considered in our study, followed by the percentile adjustments of these attributes over discipline-based research councils and years. Formally, we introduce the following notations:

1. $V(g_i)$: The funded value of grant g_i.

2. $D(g_i)$: The time duration of grant g_i.

3. $T(g_i)$: The number of investigators in grant g_i.

4. $N_p(g_i)$: The number of papers funded by the grant g_i:

$$N_p(g_i) = |Papers(g_i)| \tag{4}$$

   where $Papers(g_i)$ denotes the set of papers that funded by grant g_i.

5. $C_5(g_i)$: The total normalized citations that grant g_i accumulates from the funded papers 5 years after its publication:

$$C_5(g_i) = \sum_{p_j \in Papers(g_i)} C_5(p_j) \tag{5}$$

   where $C_5(p_j)$ represents the normalized citations that paper p_j accumulates 5 years after publication.

6. $\langle C_5(g_i) \rangle$: The average normalized citations that grant g_i accumulates from the funded papers 5 years after its publication:

$$\langle C_5(g_i) \rangle = \frac{\sum\limits_{p_j \in Papers(g_i)} C_5(p_j)}{N_p(g_i)} \tag{6}$$

Many studies have shown that: (i) the number of received citations fluctuate greatly in different disciplines, and (ii) the average number of citations per paper changes over time [4, 5, 6]. Thus, we here follow the authoritative approach [4] and normalize the citations of each paper by the average citations of all papers belonging to the same year and discipline (including 19 scientific disciplines in Microsoft Academic Graph (MAG) dataset).

Supplementary Figure 10 illustrates that the six attributes of research projects vary greatly among different councils, especially in terms of average funded value and average number of reported publications. For instance, the average number of publications per grant in STFC is nearly fifteen times larger than that in AHRC. In order to fairly compare grant properties and research outcomes across different research council and year, we adjust these features by calculating their percentile rank relative to the values in the same council and year. More formally, let $P(X(g_i))$ denote the percentile rank of a considered feature value of grant g_i relative to a list of grants in the same council and year, where $X \in \{V, D, T, N_p, C_5, \langle C_5 \rangle\}$. For example, $P(V(g_i)) = 80$ means that 80% of the observed grant value are below the given value of grant g_i; Similarly, $P(T(g_i)) = 30$ indicates that 30% of grant team size are smaller than that of the given grant g_i. In this way, the attributes of research grants awarded by different research councils and years are comparable.

6.2 PIs' Funding performance and research outcomes

After obtaining the features of research grants, we then quantify the funding performance and research outcomes for any given principal investigators s_k based on their involved grants in an observing period. Here, we introduce the following notations:

1. $N_g(s_k)$: The number of grants obtained by principal investigator s_k:

$$N_g(s_k) = |Grants(s_k)| \tag{7}$$

   where $Grants(s_k)$ denotes the set of research grants that obtained by investigator s_k in a given time period.

2. $R(s_k)$: The institution ranking of principal investigator s_k. Here, we measure institutions' ranking based on their total awarded amounts of funding from 2006 and 2018. We only consider the institutions at least receiving 5 research grants during the period, and there are a total of 199 scientific institutions.

3. $\langle P(X(g_i)) \rangle_{s_k}$: The average percentile features of grants obtained by principal investigator s_k:

$$\langle P(X(g_i)) \rangle_{s_k} = \frac{\sum\limits_{g_i \in Grants(s_k)} P(X(g_i))}{N_g(s_k)} \tag{8}$$

   where $X \in \{V, D, T, N_p, C_5, \langle C_5 \rangle\}$, referring to the six attributes of research grants mentioned above. For example, $\langle P(V(g_i)) \rangle_{s_k}$ indicates the average percentile funded value across research grants received by principal investigator s_k. Similarly, the average percentile of total normalized citations per project led by investigator s_k is defined as $\langle P(C_5(g_i)) \rangle_{s_k}$.

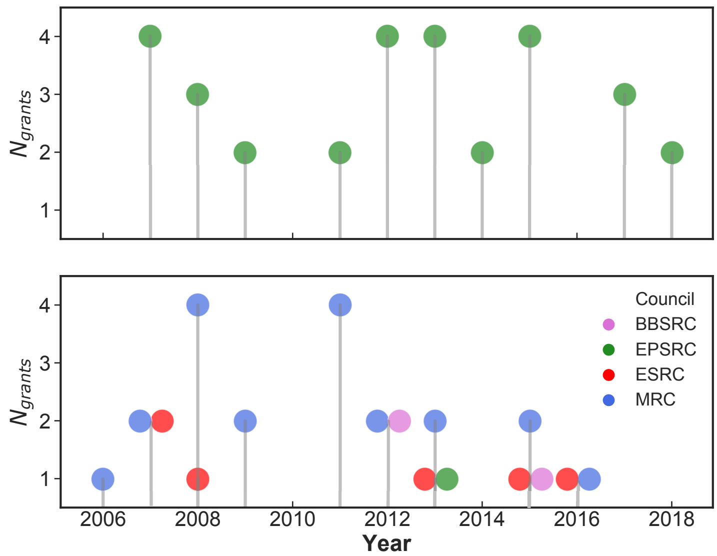
Based on these metrics, we are able to compare research outcomes and performance in funding between each paired investigators.

7 Supplementary Note 7: Robustness check for different definitions of interdisciplinarity

To check whether our results are robust under different definition of interdisciplinarity, we perform the further examination by using the fields defined for MAG dataset. Specifically, we calculate the number of different fields N_{field} in which principal investigators published their papers. Supplementary Figure 15 shows that the papers published by cross-council investigators span a wider range of research fields, confirming that the cross-council investigators are more multi-disciplinary.

Moreover, we dig deeper into the MAG dataset by examining the relationship between the number fields that researchers published in and their citation impact and future funding performance. In the former case, the results show an inverted U-shape between the number of fields and normalised citations (Supplementary

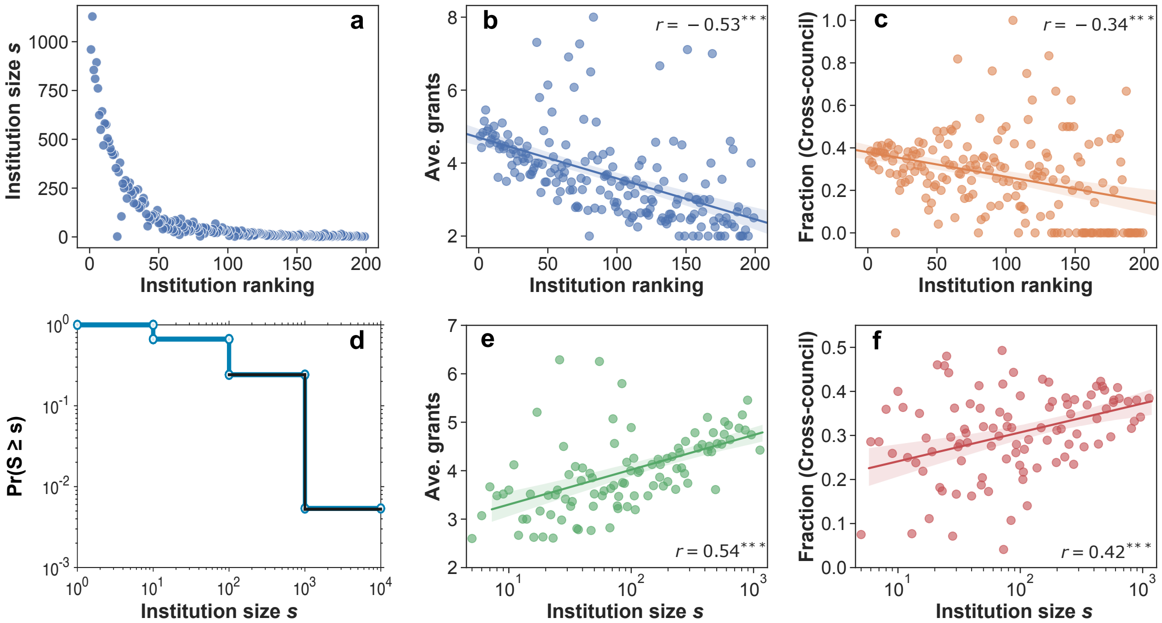
Figure 16), which is consistent with previous studies that adopted more elaborate metrics to quantify interdisciplinarity [7, 8]. We also find a strong positive correlation between the number of fields and future funding performance (Supplementary Figure 17). Overall, we believe these results to be very much consistent with those in our findings, as they show that impact declines with a certain degree of interdisciplinarity, and that funding performance is instead improved by it.



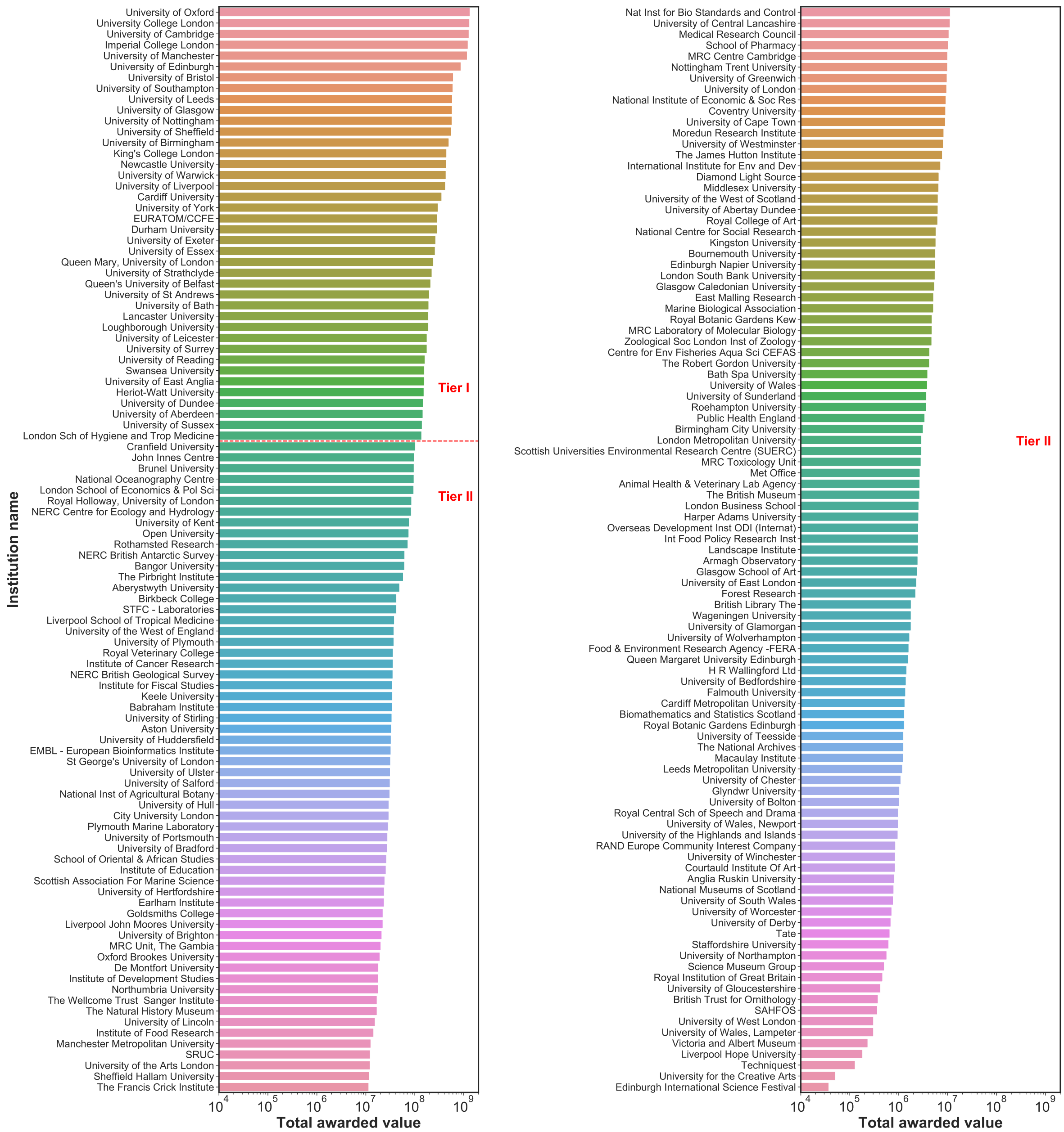
Supplementary Figure 1: **The awarded grant history of two investigators.** Both investigators have obtained 30 research grants throughout the studied period, but one has only received funding from *EPSRC* (within-council; top panel) and the other has received funding from four different research councils (cross-council; bottom panel), namely *BBSRC*, *EPSRC*, *ESRC* and *MRC*. Here, the research projects in which the two investigators were involved as PIs and CIs have been documented.

Supplementary Table 1: **Summary of research projects in seven research councils between** 2006 **and** 2018**.** N_g represents the number of research grants. V indicates the total amount of funding allocated to each council. N_{inv}, N_{ins} and N_{sub} denote the number of different investigators, research institutions and subjects, respectively.

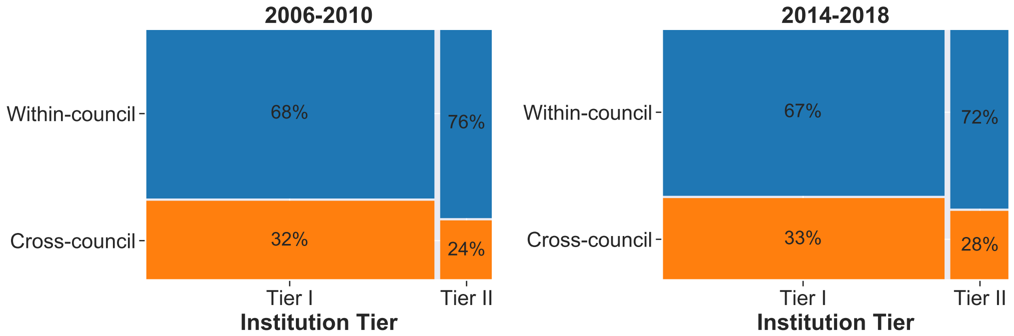
Research Council	Abbr.	N_g	$V(\times 10^9)$	N_{inv}	N_{ins}	N_{sub}
Arts and Humanities Research Council	AHRC	$4,488$	0.8	$6,160$	158	63
Biotechnology and Biological Sciences Research Council	BBSRC	$7,878$	3.0	$6,573$	149	54
Economic and Social Research Council	ESRC	$4,910$	1.9	$9,849$	187	62
Engineering and Physical Sciences Research Council	EPSRC	$13,712$	8.2	$13,332$	153	68
Medical Research Council	MRC	$4,507$	3.6	$10,004$	162	22
Natural Environment Research Council	NERC	$5,879$	1.6	$5,398$	197	71
Science and Technology Facilities Council	STFC	$3,045$	1.4	$2,428$	172	58



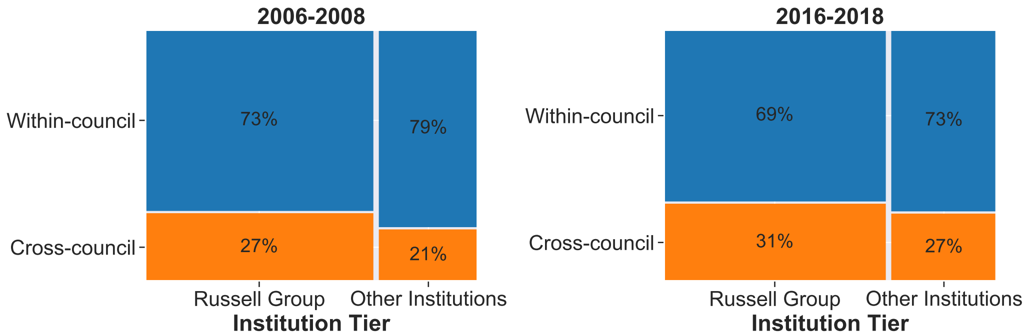
Supplementary Figure 2: **Basic features of research institutions.** **(a)** The institution size against the institutional ranking, where the institution size is determined by the total number of distinct investigators that obtained at least one research grant under the institution, and the institution ranking is measured by the total amount of research grants awarded to an institution between 2006 and 2018. **(b)** The average number of grants obtained by each investigator generally decreases with the ranking of one's affiliation. **(c)** The correlation between institution ranking and the fraction of cross-council investigators is reported. **(d)** Empirical distribution of institution size s (blue line), along with the best fitting power-law distribution (black line) with the lower bound $b_{min} = 100$ at the tenth bin boundary and scaling parameter $\alpha = 2.66$. **(e)** The average number of grants obtained by each investigator positively correlates with the ranking of one's affiliation, indicating that the investigators in large institutions are likely to obtain more research grants on average. **(f)** A positive correlation between institution size and the fraction of cross-council investigators. The statistical model used to estimate a linear regression in **e-f** is in the form of $y \sim log(x)$. The solid line and the shaded area represent the regression line and the 95% confidence interval, respectively. Each regression has also been annotated with the corresponding Pearson's r with $***p < 0.001$.



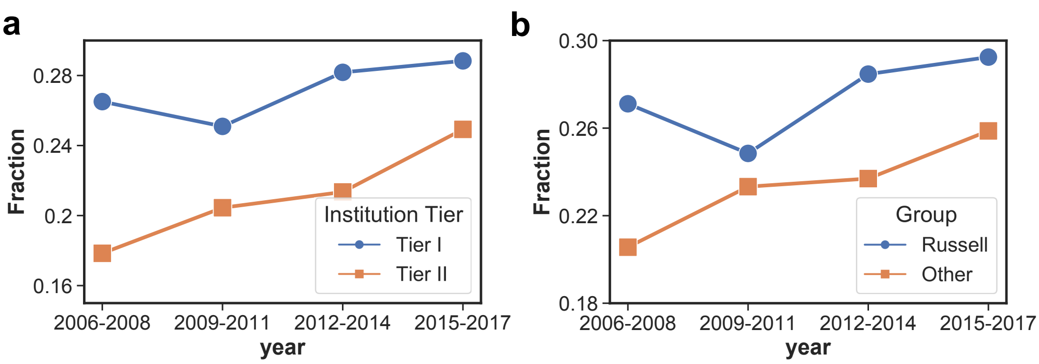
Supplementary Figure 3: **Institutional ranking and stratification.** The research institutions are ranked according to their total awarded funding amount from 2006 to 2018. Here, we consider 199 research institutions who have received at least 5 research grants from the seven national research councils. The institutions are stratified into two tiers by checking whether their total awarded funding value is larger than the average amount per institution (i.e., 1.02×10^8 marked with dashed red line).



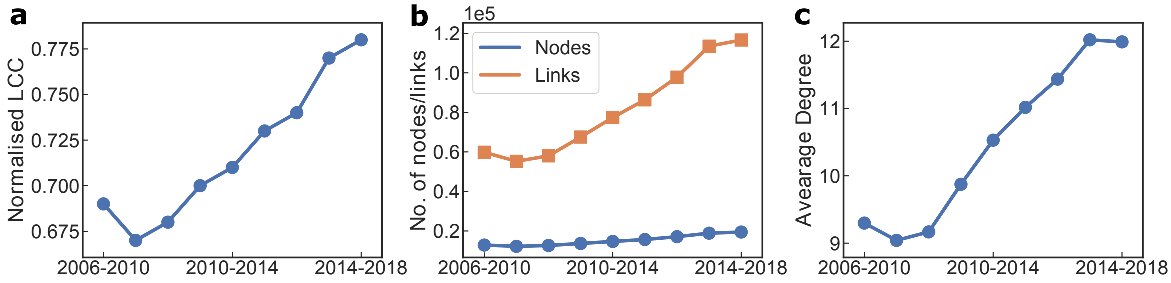
Supplementary Figure 4: **The percentage of cross-council investigators in two compared 5-year time windows.** Here, the research institutions are stratified into two tiers by checking whether their total awarded funding is larger than the average amount per institution (i.e., 1.02×10^8). Box widths are proportional to the number of investigators in Tier I and Tier II, respectively. Box heights are proportional to the percentage of cross-council and within-council investigators. The institutions in Tier I have higher proportions of cross-council investigators than that in Tier II in both 5-y time windows (χ^2 test $p < 0.0001$, odds ratio$= 1.49$ for 2006-2010; $p < 0.0001$, odds ratio$= 1.28$ for 2014-2018).



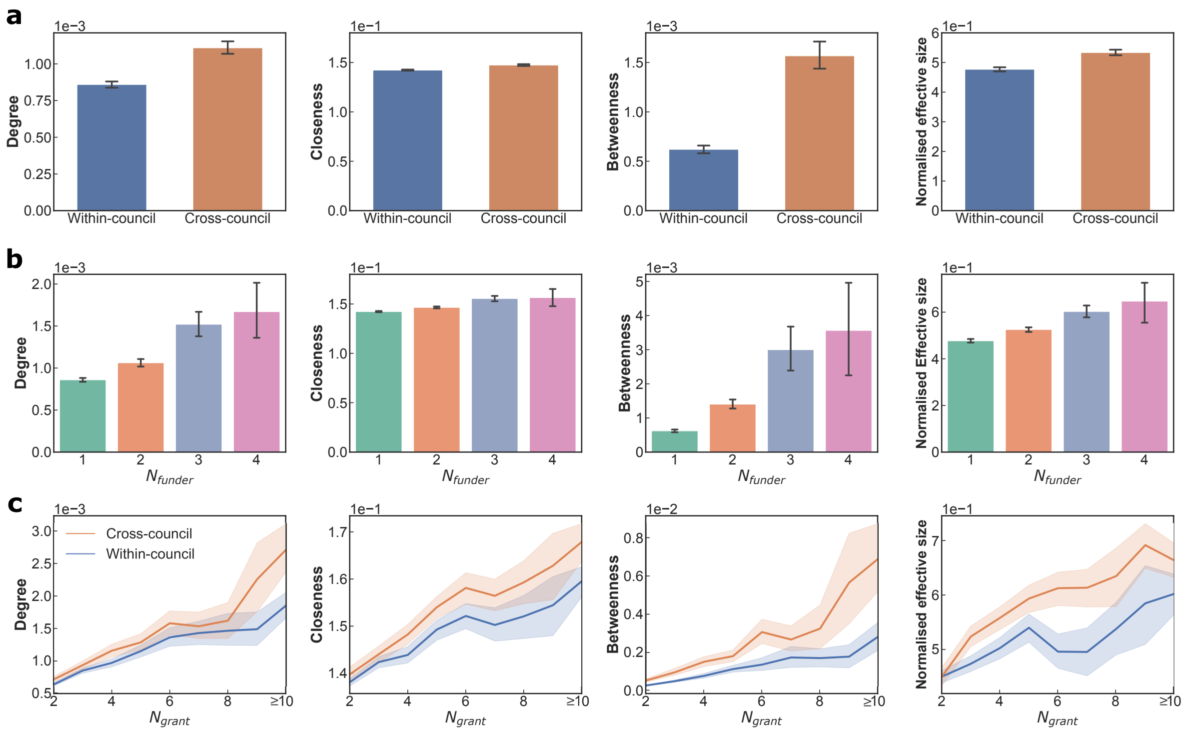
Supplementary Figure 5: **The percentage of cross-council investigators in Russell group and other institutions.** Here, the research institutions are stratified into two groups: the Russell Group and other institutions. Box widths are proportional to the number of investigators in Tier I and Tier II, respectively. Box heights are proportional to the percentage of cross-council and within-council investigators. The institutions in Russell group have higher percentages of cross-council investigators than that in the other institution group in both 3-y time windows (χ^2 test $p < 0.0001$, odds ratio$= 1.44$ for 2006-2010; $p < 0.0001$, odds ratio$= 1.21$ for 2016-2018).



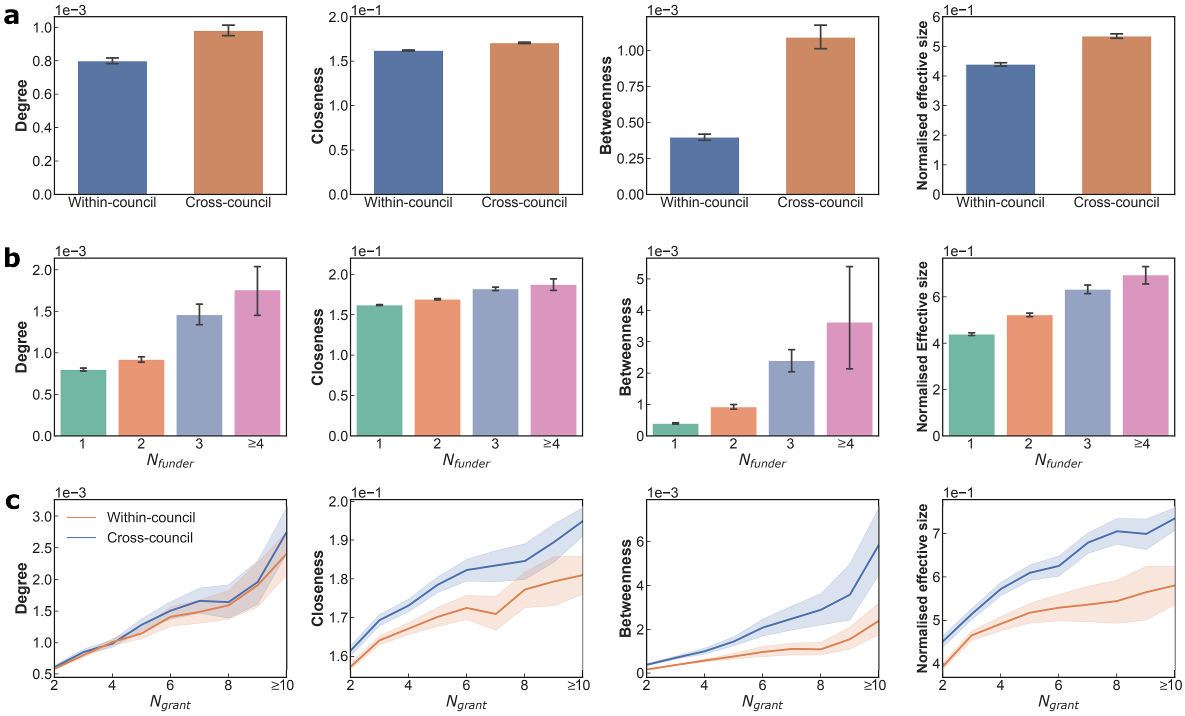
Supplementary Figure 6: **The fractions of cross-council investigators in different institutional tiers and periods.** (a) The research institutions are stratified into two tiers by checking whether their total awarded funding is larger than the average amount per institution (i.e., 1.02 × 108). (b) The research institutions are grouped into Russell universities and other institutions.



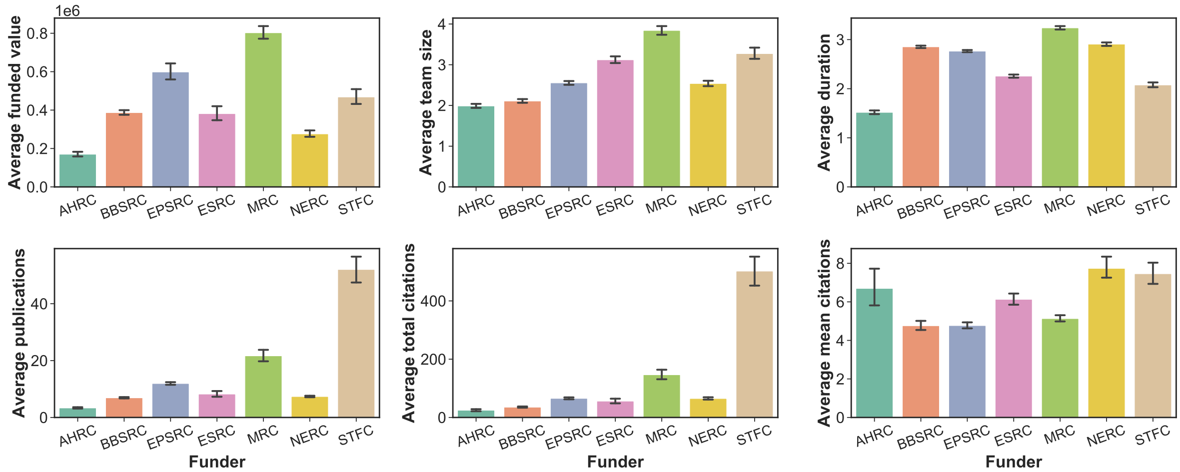
Supplementary Figure 7: **Network properties of the collaboration network for each 5-y sliding time window between** 2006 **and** 2018**.** (a) The normalized LCC grows over time, indicating the collaboration network becomes more interconnected. The normalized LCC is calculated by dividing the size of the LCC by the total number of nodes in the network. (b) The number of nodes and links in the collaboration network. (c) The average degrees of collaboration network increase over time.



Supplementary Figure 8: **Network structural advantages of cross-council investigators between** 2006 **and** 2010**.** Each column corresponds to a different network property, namely (from left to right): the degree centrality, closeness centrality, betweenness and normalized effective size. **(a)** Cross-council investigators significantly outperform the within-council investigators in four network properties (Welch's t-test $p < 0.001$). **(b)** Network metrics among investigators increase with the number of councils (N_{funder}) they have received funding from. **(c)** Cross-council investigators consistently outperform within-council investigators, regardless of the number of grants (N_{grant}) they have obtained in the period. The same applies in the case of the degree only for investigators who receive large numbers of grants. The error bars and shaded areas both represent 95% confidence intervals.



Supplementary Figure 9: **Network structural advantages of cross-council investigators between** 2014 **and** 2018**.** Each column corresponds to a different type of network properties, namely (from left to right): the degree centrality, closeness centrality, betweenness and normalized effective size. **(a)** Cross-council investigators significantly outperform the within-council investigators in four network properties (Welch's t-test $p < 0.001$). **(b)** Network metrics among investigators increase with the number of councils (N_{funder}) they have received funding from. **(c)** Cross-council investigators consistently outperform within-council investigators in terms of closeness, betweenness and normalized effective size, regardless of the number of grants (N_{grant}) they have obtained in the period. The error bars and shaded areas both represent 95% confidence intervals.



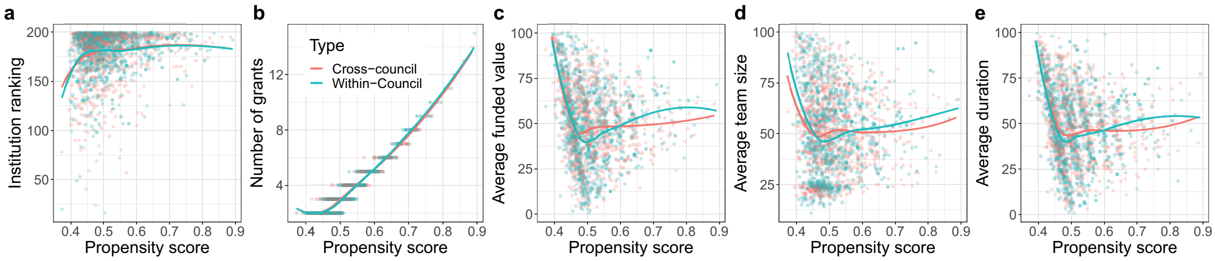
Supplementary Figure 10: **Comparison of project properties and outcomes between the seven research councils.** We compare six different characteristics of research projects as follows: (1) the average funded value per grant; (2) the average team size across the awarded grants; (3) the average duration per project; (4) the average number of publications reported per project; (5) the average total citations of papers received within 5 years of publication across funded projects; and (6) the average mean citations of papers received within 5 years of publication across funded projects. The attributes of research projects vary greatly among different councils, especially in terms of average funded value and average number of reported publications. Error bar represents the 95% confidence interval.

Supplementary Table 2: **Regression analysis of cross-council behavior on research outcomes and scientific impact.** Along with each indicator of outputs, the following predictor variables were used: PI's institutional ranking, the number of awarded grants and their average value, team size and duration. The regression models are computed in matched datasets. Standard errors for the coefficients are reported in parenthesis. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

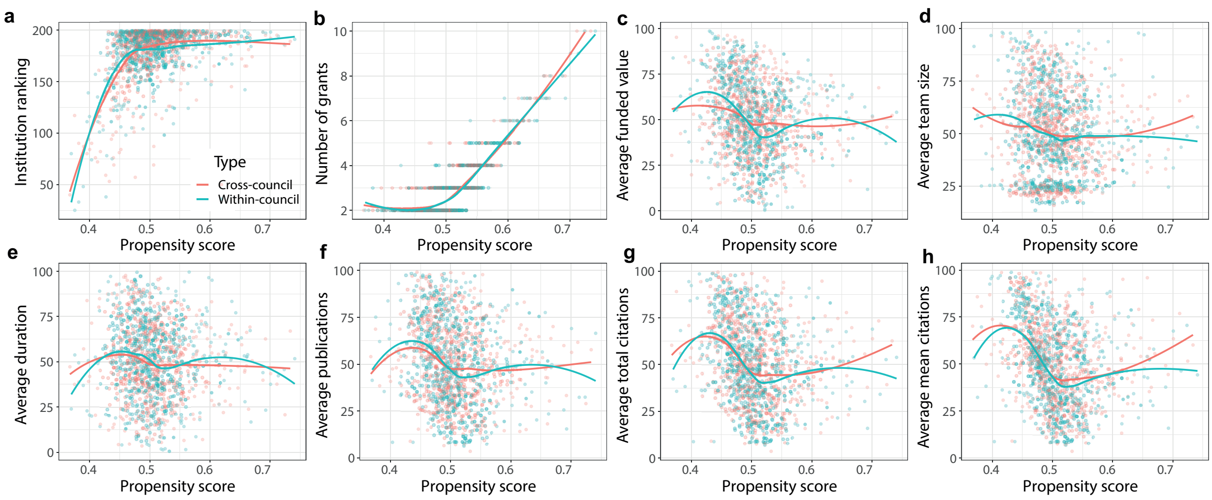
	Dependent variables: research outcomes and scientific impact		
	Average papers	Average total citations	Average mean citations
Cross-council	-1.92^{**}	-3.37^{***}	-3.65^{***}
	(0.86)	(0.86)	(1.00)
Institution ranking	-0.03^{*}	-0.04^{**}	-0.04^{*}
	(0.02)	(0.02)	(0.02)
Number of grants	0.25	0.42	0.39
	(0.24)	(0.26)	(0.28)
Average funded value	0.30^{***}	0.29^{***}	0.15^{***}
	(0.03)	(0.03)	(0.03)
Average team size	0.05^{**}	0.07^{***}	0.04
	(0.02)	(0.02)	(0.03)
Average duration	0.19^{***}	0.12^{***}	-0.01
	(0.03)	(0.03)	(0.03)
Constant	24.50^{***}	28.77^{***}	42.95^{***}
	(1.76)	(1.87)	(2.03)
No. of pairs	958	958	958
Adjusted R^2	**0.21**	**0.15**	**0.03**

Supplementary Table 3: **Regression analysis of cross-council behavior on long-term funding performance.** Along with each dependent variable of funding performance, the following dependent variables were used: PI's institutional ranking, the number of awarded grants and their average value, team size, duration, the number of publications, total citations and mean citations. The regression models are computed in matched datasets. Standard errors for the coefficients are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

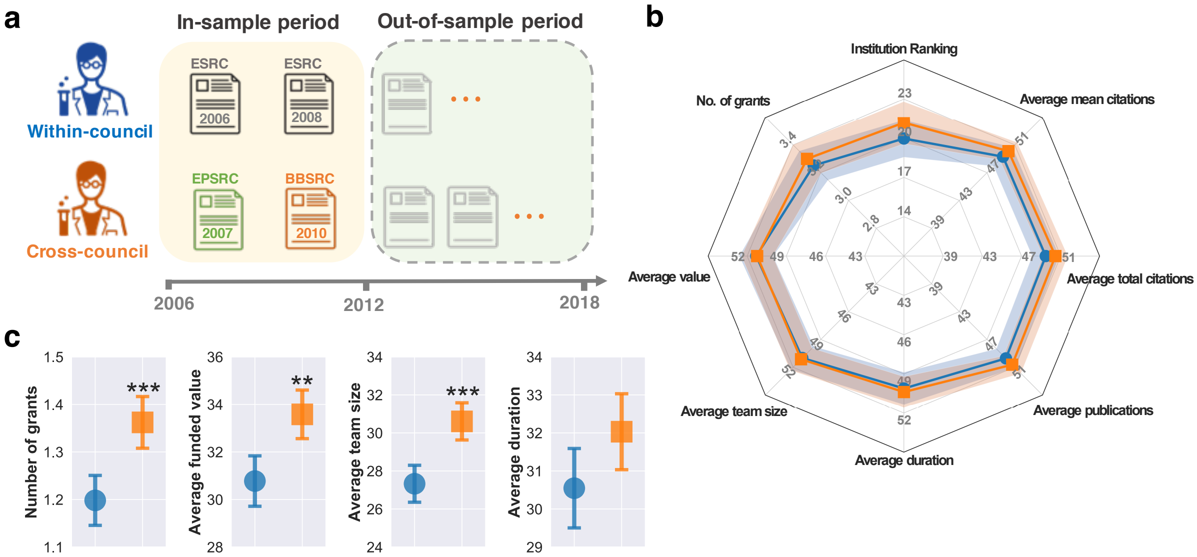
	Dependent variables: funding performance in out-of-sample period			
	Number of grants	Average funded value	Average team size	Average duration
Cross-council	0.23^{**}	3.35^{**}	3.68^{**}	1.24
	(0.10)	(1.60)	(1.56)	(1.62)
Institution ranking	-0.003	-0.07^{**}	-0.01	-0.04
	(0.002)	(0.03)	(0.03)	(0.03)
Number of grants	0.60^{***}	4.19^{***}	4.04^{***}	4.15^{***}
	(0.04)	(0.61)	(0.59)	(0.61)
Average funded value	0.001	0.21^{***}	-0.03	0.02
	(0.004)	(0.06)	(0.05)	(0.06)
Average team size	0.002	0.11^{**}	0.32^{***}	0.06
	(0.002)	(0.04)	(0.04)	(0.04)
Average duration	0.01^{*}	-0.0007	0.05	0.11^{**}
	(0.003)	(0.05)	(0.05)	(0.05)
Average publications	-0.01^{*}	0.10	0.05	0.13
	(0.01)	(0.13)	(0.13)	(0.13)
Average total citations	0.03^{**}	0.17	0.24	0.16
	(0.01)	(0.21)	(0.21)	(0.21)
Average mean citations	-0.02^{*}	-0.11	-0.15	-0.08
	(0.01)	(0.12)	(0.12)	(0.12)
Constant	-0.70^{***}	-0.07	-3.06	3.90
	(0.25)	(3.85)	(3.75)	(3.88)
No. of pairs	709	709	709	709
Adjusted R^2	**0.17**	**0.10**	**0.10**	**0.08**



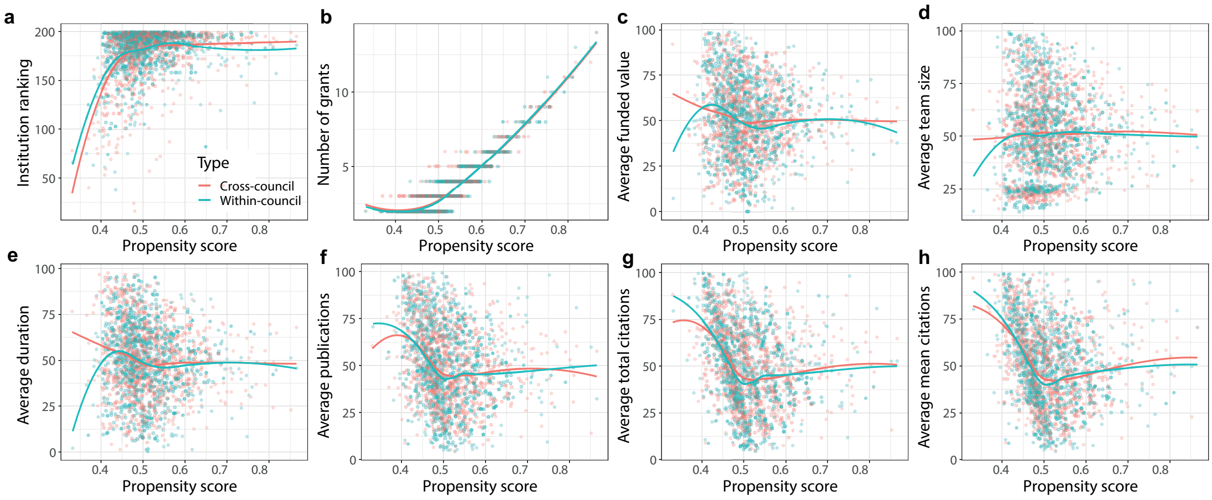
Supplementary Figure 11: **Propensity scores for matched-pair analysis.** Each plot shows the propensity scores for each PI in our matched pair analysis for the five considered confounding factors (from left to right): **(a)** institutional ranking; **(b)** the number of awarded grants; **(c)** the average funded value per grant; **(d)** the average team size across the awarded grants; and **(e)** the average duration per project. Values for cross-council investigators are shown in red, while that of the within-council investigators are shown in green. Solid lines show the average values of all covariates as functions of the propensity scores.



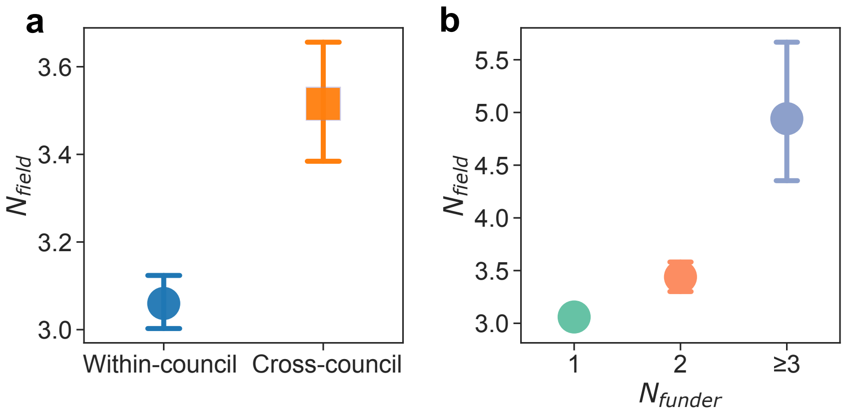
Supplementary Figure 12: **Propensity scores for matched-pair analysis.** Each plot shows the propensity scores for each PI in our matched pair analysis for all considered confounding factors in the observation period, including **(a)** institutional ranking, measured by the total amount of research grants awarded to an institution between 2006 and 2018; **(b)** the number of grants awarded; **(c)** the average funded value per grant; **(d)** the average team size across the awarded grants; and **(e)** the average grant duration; **(f)** the average number of papers reported per project; **(g)** the average number of *total* citations received per grant (calculated as the average of the total citations received by papers associated with a grant); and **(h)** the average number of citations received per paper per grant (calculated first as the average of the citations received by papers associated with a grant, and then averaged over the total number of grants awarded to a PI). Values for cross-council investigators are shown in red, while that of the within-council investigators are shown in green. Solid lines show the average values of all covariates as functions of the propensity scores.



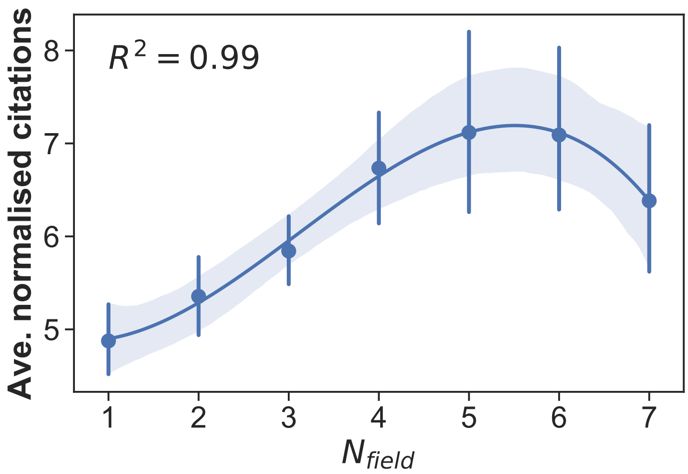
Supplementary Figure 13: **Comparing long-term funding performance between cross-council and within-council investigators.** **(a)** An illustrative example of comparison in terms of future funding performance of cross-council (orange) and within-council (orange) principal investigators (PIs) with similar funding profiles. Both PIs obtained 2 research grants during the in-sample period from 2006 to 2012, but the with-council PI received grants from the same research council (both from Economic and Social Research Council (ESRC)), while the cross-council PI received grants from 2 different councils (one from Engineering and Physical Sciences Research Council (EPSRC), and the other from Biotechnology and Biological Sciences Research Council (BBSRC)). For the in-sample period 2006-2012, we pair the PIs with similar career profiles, while for the out-of-sample period 2013-2018, we compare the funding performance of each paired PIs. **(b)** Matching the cross-council and within-council PIs with similar career profiles in terms of both funding performance and research outcomes during the observation period. We matched 8 different characteristics for PIs between 2006 and 2012 as follows: institutional ranking of a given PI whereby institutions are ranked by their total amount of funding between 2006 and 2018, the number of grants a given PI has received, and among these projects, the average grant value, the average team size, and the average project duration, the average number of publications reported , the average number of *total* citations received per grant (calculated as the average of the total citations received by papers associated with a grant), and the average number of citations received per paper per grant (calculated first as the average of the citations received by papers associated with a grant , and then averaged over the total number of grants awarded to a PI). There is no statistically significant difference between the two groups of PIs across the eight factors following the pairing. **(c)** Difference in long-term funding performance between cross-council and within-council PIs in the subsequent 6 years (from 2013 to 2018). Cross-council PIs outperform within-council PIs in grant volume, value and team size. The significance levels shown refer to t-tests and Kruskal–Wallis tests. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. Error bar represents the standard error of the mean.



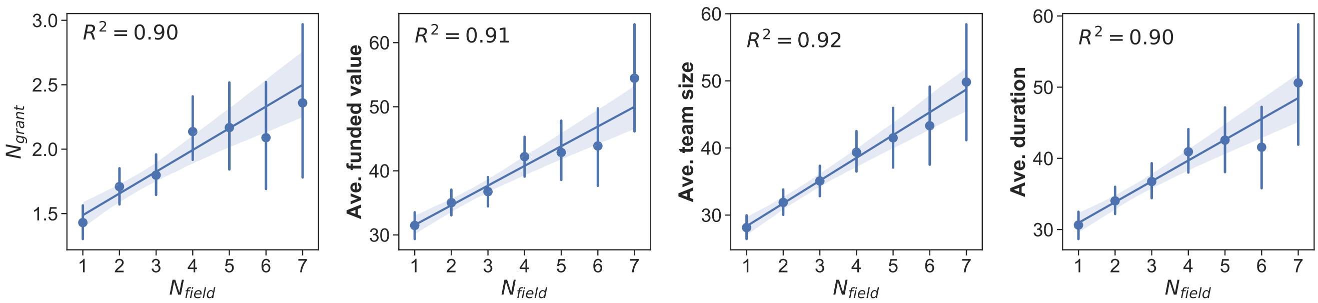
Supplementary Figure 14: **Propensity scores for matched-pair analysis.** Each plot shows the propensity scores for each PI in our matched pair analysis for all considered confounding factors in the observation period, including **(a)** institutional ranking, measured by the total amount of research grants awarded to an institution between 2006 and 2018; **(b)** the number of grants awarded; **(c)** the average funded value per grant; **(d)** the average team size across the awarded grants; and **(e)** the average grant duration; **(f)** the average number of papers reported per project; **(g)** the average number of total citations received per grant (calculated as the average of the total citations received by papers associated with a grant); and **(h)** the average number of citations received per paper per grant (calculated first as the average of the citations received by papers associated with a grant, and then averaged over the total number of grants awarded to a PI). Values for cross-council investigators are shown in red, while that of the within-council investigators are shown in green. Solid lines show the average values of all covariates as functions of the propensity scores.



Supplementary Figure 15: **(a)** The papers published by cross-council PIs span a wider range of research fields (t-test p-value $<3 \times 10^{-8}$). N_{field} indicates the number of different fields in which PIs published their papers, where all the papers have been classified into 19 scientific disciplines in Microsoft Academic Graph (MAG). **(b)** The number of research fields (based on the classification by MAG dataset) in which PIs have published their papers increases with the number of councils they have received funding from.



Supplementary Figure 16: **The relationship between the interdisciplinarity of PIs and their citation impact.** The interdisciplinarity of investigators (measured by the number of different research fields N_{field} in which they published their papers in Microsoft Academic Graph) shows an inverted U shape relation with citation impact, indicating that the moderate interdisciplinary investigators have higher citation impact.



Supplementary Figure 17: **The relationship between PIs' interdisciplinarity and their future funding performance.** Here, we quantify the interdisciplinarity of PIs by the number of different research fields N_{field} in which they published their papers in MAG. Results show that PIs' performance in terms of number, value and team size of grants increases with the number of fields they have spanned.

Supplementary References

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