Comparing the outputs of intramural and extramural grants funded by National Institutes of Health

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Abstract

Funding agencies use a variety of mechanisms to fund research. The National Institutes of Health in the United States, for example, employs scientists to perform research at its own laboratories (intramural research), and it also awards grants to pay for research at external institutions such as universities (extramural research). Here, using data from 1594 intramural grants and 97054 extramural grants funded between 2009 and 2019 , we compare the scholarly outputs from these two funding mechanisms in terms of number of publications, relative citation ratio and clinical metrics. We find that extramural awards more cost-effectively fund outputs commonly used for academic review such as number of publications and citations per dollar, while intramural awards are more cost-effective at generating work that influences future clinical work, more closely in line with agency health goals. These findings provide evidence that institutional incentives associated with different funding mechanisms drive their comparative strengths.

Introduction

National funding agencies have a responsibility to ensure that the research projects they fund are successful, as measured by various metrics (such as number of scientific papers, number of early-career researchers trained, and societal and/or economic impact). Many of these agencies run their own research laboratories (intramural research) and also fund research at universities and other institutions

(extramural research). Certain aspects of the grant funding system have been the focus of research (Azoulay, Zivin, & Manso, 2009; Goldstein & Kearney, 2020; Hoppe et al., 2019; Lauer, Roychowdhury, Patel, Walsh, & Pearson, 2017; Wahls, 2018a, 2018b), notably efforts to reduce various forms of bias, but the relative merits of intramural and extramural funding have received little attention to date.

The United States National Institutes of Health is one of the largest funders of research in the world. It comprises 27 institutes and centers (24 of which fund grants), each with its own research agenda often related to a specific disease (such as the National Cancer Institute and the National Institute of Allergy and Infectious Diseases). In Fiscal Year 2022, the NIH spent approximately $5 billion on intramural research at its own laboratories, and $39 billion on extramural research at universities, medical schools and research institutes across the US (https://www.nih.gov/about-nih/organization/budget). Extramural grants are generally investigator-initiated applications that are assigned to and reviewed by peers at a topically appropriate Study Section panel before final funding decisions are made by NIH based on those scores. Intramural funding is in large part a retrospective review of an NIH intramural investigator by an external Board of Scientific Counselors based on their past performance and possible future directions, and research is conducted by a combination of postdoctoral fellows and staff scientists. Questions about the most effective portfolio management approaches have been an ongoing source of contention (Supplemental Text).

Here, using data from 1594 intramural grants and 97054 extramural grants, we compare the distribution of research topics funded by the two mechanisms (Figure 1), and the values of the grants awarded under each mechanism (Figure 2). The large difference in the number of intramural vs. extramural awards is reflective of the larger size of Intramural awards compared to Extramural awards, combined with the much smaller proportion of the funding portfolio dedicated to Intramural research. We also use five metrics to analyze the 621,138 papers that acknowledge at least one of these projects: number of papers; relative citation ratio, which is a field- and time-normalized measure of scientific influence; approximate potential to translate, which is a machine-learning prediction that a given paper will be cited by a clinical article; total clinical citation counts; and a binary measure of the number of papers that received at least one clinical citation (Figure 3). We also compare the cost effectiveness of the two approaches by, for example, comparing the average cost of each paper published (Figure 4), and also explore the influence of various factors, such as the high costs associated with human-focused research (Figure 5).

A potential advantage of the extramural approach is that cost-sharing at universities may increase the scientific return on the NIH's investment. Potential advantages of the intramural approach are that researchers in the NIH's own laboratories allow the NIH to hire researchers whose research agendas more closely align with its mission.

This study is not without limitations. First, data about the intramural portfolio is only available from post-2008, which constrains the time frame for this study. Second, collaboration between intramurally and extramurally funded scientists introduces complexity to the comparative analysis, leading to the exclusion of jointly funded publications.

Results

Comparison of research topics for intramural and extramural projects

Our analyses reveal differences in the research topics investigated by researchers funded by the two mechanisms. By clustering publications based on their titles and abstracts, we find that intramural projects yield a higher-than-average number of publications on viral infection, cancer and genes, and a lower-than-average number of papers on adolescents, brain studies and maternal health (Figure 1 and Supplemental Figures 1 and 2). The overrepresentation of viral research is likely because of the outsize investment toward the intramural Vaccine Research Center, and the cancer/genetics overrepresentation due in part because National Cancer Institute intramural investigators conduct research at that institute as well as at the NIH Clinical Center for their human genetics work.

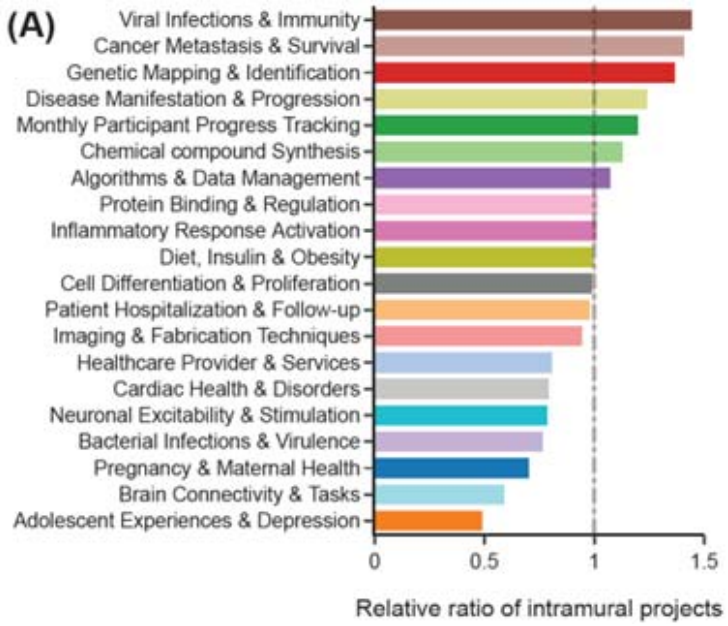

Figure 1. Research topics for intramural and extramural projects.

The topics listed were identified by clustering publications based on their titles and abstracts via Word2Vec (see Methods). The relative ratio of intramural projects for each topic was calculated by taking a ratio of the proportions of total grants a topic represented in the intramural vs. extramural portfolios. A relative ratio >1 signifies a higher share of intramural project publications on that topic relative to their share across all topics. For example, if a topic comprised 10% of grants in the intramural portfolio but only 5% of grants in the extramural portfolio, this would represent a 2:1 intramural:extramural relative ratio, or 2.0.

Comparison of funding for intramural and extramural projects

Next we compared funding for intramural and extramural research projects, and found that annual funding for extramural research projects was consistently lower than that for intramural research projects (Figure 2). Indeed, the average funding for extramural projects remained roughly constant, at below $500k per year between 2009 and 2019, whereas the average funding for intramural projects increased from about $0.42 million to about $0.45 million over the same period. Given that NIH funding for intramural research has remained relatively constant as a percent of total funding over the years, this indicates larger single awards for intramural research while extramural investigators may increasingly require multiple concurrent grants to sustain their labs.

This finding is consistent with the intramural research requiring higher financing due to the absence of cost-sharing with universities. It also reflects observations that extramural researchers need multiple federally funded grants to sustain a lab. While such institutions do receive audited indirect costs to cover overhead associated with research (Culliton, 1992), recent research indicates that significant cost-sharing greatly influences scientific productivity. Specifically, the extent of universities subsidies for student labor costs is a direct factor in university productivity (Zhang, Wapman, Larremore, & Clauset, 2022). In contrast to extramural awards, intramural funding as reviewed by the Board of Scientific Counselors and each Institute's scientific Director, can in principle fund an entire lab through a single, larger award. This frees the intramural investigators from the time commitment of securing grants. However, running in-house labs does entail that there is no cost sharing with external institutions, potentially raising the cost of such research (Culliton, 1992; Korn, 2015; Macilwain, 1999; Zhang et al., 2022).

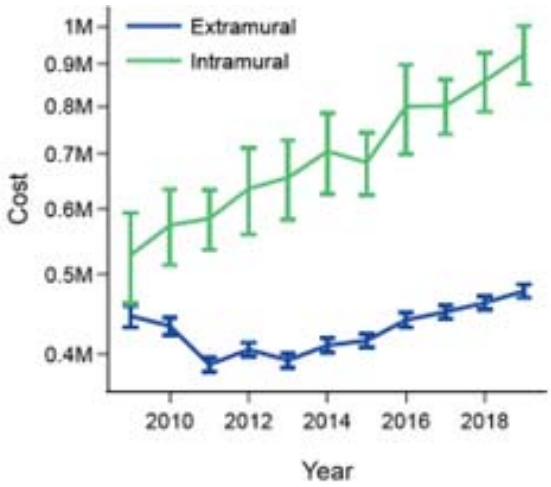

Figure 2. Project funding for intramural and extramural projects.

(A) Mean project cost (on a log scale) versus year for intramural grants (green) and extramural grants (red) between 2009 and 2019. Error bars denote 95% confidence intervals. Total costs were used rather than only direct costs in order to fully account for the degree of government investment. Error bars are larger for intramural data because of the smaller total number of awards (98,648 extramural and 1594 intramural).

Comparison of outputs from intramural and extramural projects

Next we used five metrics related to publications and citations – number of papers; relative citation ratio (Hutchins, Hoppe, Meseroll, Anderson, & Santangelo, 2017; Hutchins, Yuan, Anderson, & Santangelo, 2016); approximate potential to translate (Hutchins, Davis, Meseroll, & Santangelo, 2019); total clinical citation counts (Hutchins, Baker, et al., 2019; Hutchins, Davis, et al., 2019; iCite, Hutchins, & Santangelo, 2019); and a binary measure of clinical citations – to compare the outputs of intramural and extramural projects on a year-by-year basis (Figure 3). For all of the metrics apart from total clinical citation counts, intramural research scored highest before 2010, but the gap between intramural and extramural research had closed by 2020. This increased early productivity for intramural projects, which coincides with both the typical length of an extramural award as well as the time between intramural Board of Scientific Counselors reviews, may reflect the extra attention intramural investigators are afforded due to a lack of teaching and grant writing responsibilities. The period when the gap closes occurs after the typical funding period has ended, and papers using the data and materials acquired during that period are written and cycle through peer review.

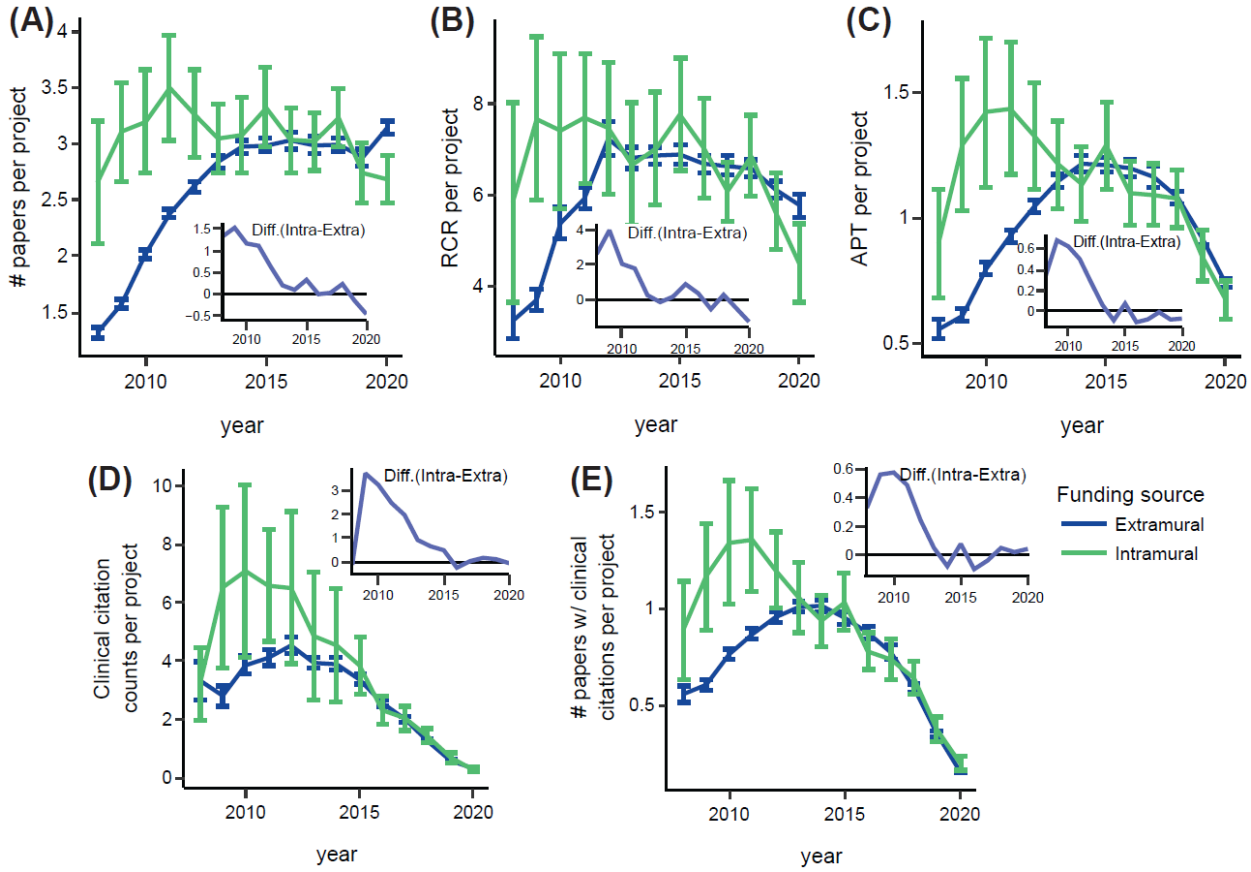

Figure 3. Annual outputs from intramural and extramural projects.

(A) Mean number of papers per project for intramural projects (green) and extramural projects (blue) between 2008 and 2020. The difference (inset) was close to 1.5 papers per project in 2008, but this gap closed over time. (**B**) Relative citation ratio per project. (**C**) Approximate potential to translate (ATP) per project. (**D**) Clinical citation counts per project. (**E**) Number of papers with at least one clinical citation per project. Error bars denote 95% confidence intervals. Error bars are larger for intramural data because of the smaller total number of awards (98,648 extramural and 1594 intramural).

Comparison of cost effectiveness for intramural and extramural projects

So far we have seen that the average funding for intramural projects is higher than that for extramural projects (Figure 2), and that intramural projects also score higher than extramural projects on the five metrics for the outputs from a project that we computed (Figure 3). Next, therefore, we compare cost effectiveness by calculating the average cost of each published paper, and likewise for the other four publication/citation metrics (Figure 4A). We do this for projects of different durations: 1–3 years, 4–6 years, and 7–10 years.

Our analysis suggests that extramural research is more cost-effective than intramural research when considering number of papers, relative citation ratio and approximate potential to translate. However, when considering metrics based on clinical citations, the gap was smaller, and for some project durations, intramural research was as cost-effective as extramural research.

Some types of research are more expensive rather others (for example, animal research is more expensive than cell biology research, and human-focused research has higher regulatory overhead costs due to increased ethical concerns), so we decided to explore if such factors could explain some of the differences that we had observed between intramural and extramural projects. To do this we conducted a regression analysis that controlled for project topic and various factors related to the principal investigator who had received the grant.

Figure 4B shows a plot of the number of years that elapsed since the start of the grant (Progression year, x-axis) and the relative cost effectiveness of intramural vs. extramural grants at funding each metric measured (#papers, red; RCR, purple; APT, yellow; #clinical citations, blue; and #papers with at least one

clinical citation, green). Each curve was a subset of the data frame focusing on each measure individually. These were generated by comparing the difference in regression coefficients of extramural vs. intramural research once controlling for grant, investigator and collaboration variables (for regression model details, see Methods). Curves above 1.0 indicate a comparative cost effectiveness advantage for extramural grants on that measure, while those below 1.0 indicate a comparative cost effectiveness advantage for intramural grants on that measure. We observe that over time, extramural and intramural grants show opposite patterns. Extramural grants excel in terms of cost advantage at measures commonly used in academic performance assessment (e.g. number of papers and citations). Intramural grants in comparison excel in cost advantage in measures more closely aligned with the NIH agency mission (i.e. knowledge that informs work to improve human health via knowledge flow to clinical trials).

We also performed propensity score matching between intramural and extramural projects by pairing each intramural project with its closest extramural counterpart (Figure 4C), and with its four closest extramural counterparts (Figure 4D). This allows us to sample intramural and extramural grants that are similar to one another at a 1:1 (e.g. 1594 intramural grants and 1594 matched extramural grants) based on their similarity in terms of topic area, prior publication record, and prior collaboration history. This propensity score matching approach accounts for potentially hidden covariates and reduces their influence. We observe the same pattern using 1:1 propensity score matching (Figure 4C) as we did with the full dataset (Figure 4B). Likewise, using propensity score matching of 1:4 (i.e. 4 matched extramural grants for every 1 intramural grant) to increase the sample size of extramural awards yielded the same result (Figure 4D). Taken together, these results indicate that regardless of sampling strategy, cost effectiveness aligns with the primary missions of the institutions at which investigators are housed (maximum knowledge generation and flow for academic institutions, and clinically relevant knowledge generation for NIH intramural research).

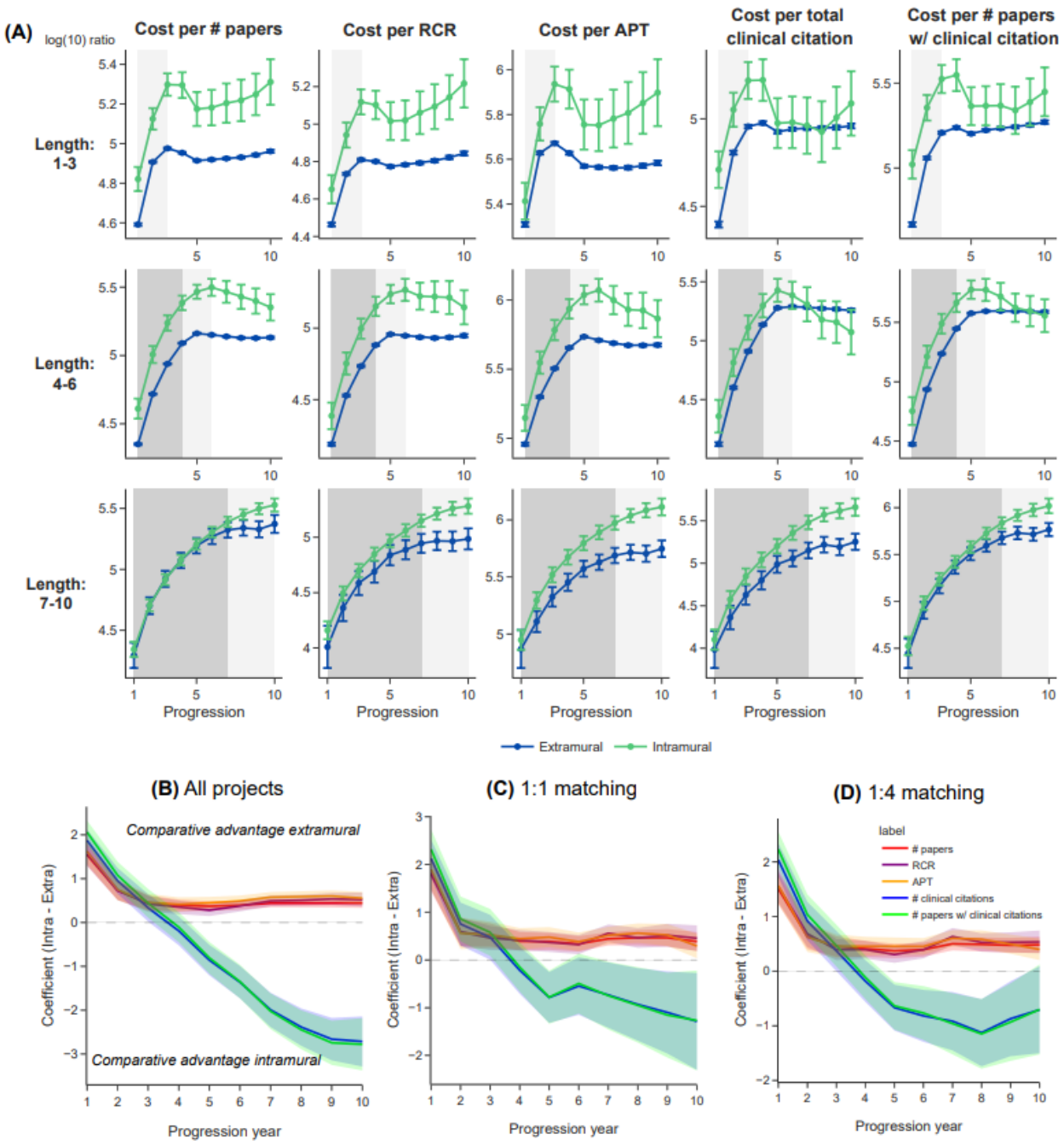

Figure 4. Cost effectiveness of intramural and extramural projects. (A) A measure of cost effectiveness versus progression (ie, year of grant) for intramural research (green) and extramural research (red), for projects of different durations: 1–3 years (top row), 4–6 years (middle), and 7–10 years (bottom). These regressions do not control for other characteristics, but rather represent the raw ratios. For the first column, the Y-axis displays $\log_{10}$(ratio) +1, where ratio is the cumulative total costs to the cumulative

total research output for each metric (cost:output, for the first column output = #papers); error bars denote the 95% confidence intervals. The remaining columns show measures of cost effectiveness for relative citation ratio, approximate potential to translate, total clinical citation counts, and a binary measure of clinical citations. To account for the fact that many papers are published after funding for the relevant grant has ended, grant amounts were multiplied by a deflator – this represents the proportion of papers published to date against the anticipated number of future publications, as determined by empirical measurements (Supplemental Table 1). In most cases, according to this analysis, extramural research is more cost effective than intramural research when observing uncontrolled regressions. **(B–D)** Linear regression results of the cost efficiency of research output measures against project types (intramural vs. extramural). The regression model was fitted for each year of the project's progression. Unlike panel (A), this regression model controls for grant, investigator, and collaboration characteristics in order to obtain a more accurate estimate of the relative cost efficiency of intramural vs. extramural projects. The Y-axis coefficient indicates the mean disparity in research output between intramural and extramural projects, controlling for these other variables (see Methods). Because there might be covariates that could confound the data, separate regressions were conducted for all projects (B, the default), and for balanced projects using 1:1 propensity score matching (1 extramural grant for every 1 intramural grant) in order to compare grants that were the most similar to reduce the influence of unobserved covariates (C) and (D) similarly to (C) 1:4 propensity matching as a robustness check. .

Comparison of scores for human-focused research, animal research, and molecular/cellular research

Next, we assign scores to papers and projects based on the extent to which they can be classified as human research, animal research or molecular/cellular research. Again, we do this for projects of different durations: 1–3 years, 4–6 years, and 7–10 years. Both intramural and extramural projects have the highest average scores for human research (Figure 5 and Supplemental Figure 3). However, long-duration intramural projects tend to have lower human scores, while long-duration extramural projects tend to have higher human scores. For animal and molecular/cellular scores, the trend is reversed: long-duration intramural projects tend to have higher animal and molecular-cellular scores, while long-duration extramural projects tend to have lower scores. The possibility that longer-term intramural projects are more human-focused, which might explain the clinical citation comparative advantage with respect to the extramural program, is therefore inconsistent with the data.

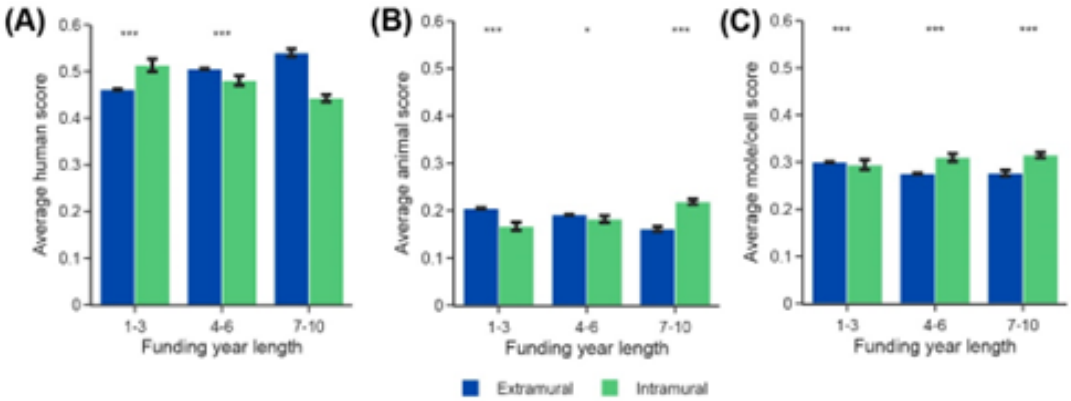

Figure 5. Comparison of scores for human-focused research, animal research, and molecular/cellular research for intramural and extramural projects.

(A-C) These represent the average Human, Animal and Molecular/Cellular scores for publications funded by extramural vs. intramural grants, respectively, which were downloaded from iCite (Hutchins, Davis, et al., 2019; iCite et al., 2019). **(A)** Average scores for human-focused research for intramural research (green) and extramural research (blue) for projects of different durations: 1–3 years (left), 4–6 years (middle), and 7–10 years (right).. **(B)** Average scores for animal research. (**C**) Average scores for molecular/cellular research. Mann-Whiteney U tests were conducted to test the difference between the scores for intramural and extramural projects. *** $p<0.001$, ** $p < 0.01$, * $p < 0.05$. No asterisk indicates the difference is not statistically significant.

Discussion

Taken together, these results demonstrate comparative advantages for extramural and intramural funding mechanisms. In particular, extramural funding seems to excel at generating raw knowledge and facilitating its downstream flow. In contrast, intramural funding mechanisms seem to have a comparative advantage at generating research, basic or human-focused, that successfully informs downstream clinical research, aligning with the agency's mission. This could potentially be attributed to the selection process for directly hiring scientists whose research agendas closely match the agency's objectives, though this aspect wasn't directly assessed in our study. However, we do rule out an obvious explanation: that more human-focused work in the intramural program is more likely to be conceptually closer to clinical trials and, therefore, have a lower barrier to entry into clinical studies (Kim, Levine, Nehl, & Walsh, 2020;

Weber, 2013). Intramural research is characterized by long-duration projects in contrast to the extramural portfolio, and these appear less human-focused than the extramural portfolio.

Critiques of NIH's grant review process often cite its conservatism, with a strong emphasis on preliminary data to mitigate project failure risks (Packalen & Bhattacharya, 2020). The recent creation of the Advanced Research Projects Agency for Health (ARPA-H) was in part for this reason (Collins, Schwetz, Tabak, & Lander, 2021). Although the high-risk, high-reward NIH portfolio seems to be largely effective at identifying and funding such projects (Tabak et al., 2019), its overall proportion of the total portfolio remains relatively small in favor of more traditional investigator-initiated research project grants. Because intramural researchers face retrospective rather than prospective review, this conservatism might be expected to manifest in a comparative advantage across a variety of measures for intramurally funded research. Competing theories suggest that extramural research may hold advantages on an investment-adjusted basis because of cost-sharing at universities, particularly for student labor (Zhang et al., 2022). Notably, Intramural research focused on human/molecular or animal research seems to be particularly effective at generating clinically relevant research outputs (Figure 5). Our findings reveal a nuanced reality: extramural institutions hold an edge in publication and citation rates aligned with their internal review procedures, while intramural research excels at stimulating bench-to-bedside translation on an investment-adjusted basis.

Methods

Data

We collected the original NIH project data from NIH RePORTER (https://exporter.nih.gov/), which contains 433,930 projects with funding information spanning from 1985 to 2019. We identified projects' activity categories by looking up their first three letters in the project number (activity code). We classified the projects into intramural and extramural projects by the initial letter of their activity codes. Specifically, projects with an activity code starting with Z were intramural projects, and other projects were extramural projects. Using this strategy, we identified 9,225 intramural projects and 424,705 extramural projects in the raw dataset. We retrieved the publication records for these projects by PMID indexed by PubMed (PubMed, 2020).

The data cleaning process is as follows. First, as the renewal of project contracts may alter the topic and arrangement of the projects, we dropped 70,297 projects with renewal records in our data. Second, considering intramural projects might change their activity categories and the three initial project number letters (e.g., ZIA changed to ZIH), we normalized 3,105 intramural project numbers by matching the rest of the project numbers to avoid inconsistency in project numbers. Third, to focus on activity categories intended as research-oriented and exclude practice-oriented activity categories, at the activity level, we selected activity categories where at least 75% of projects had produced at least one paper. This step kept 106 activity categories (including six intramural activity categories).

In this study, we focus on projects initially funded after 2008 and select the ten years from 2009 to 2019 as our analysis period. A total of 122,815 projects fell in this period. To remove the rest of potential non-research-oriented projects, at the individual project level, we selected 1% of projects with the highest cumulative ratio of funding and publication number and 1% of projects with the lowest. We then trained a random forest model to predict the projects most likely to be non-research-oriented based on their title and abstracts. Based on the predicted probability, we excluded 5% of intramural (84) and extramural (5,347) projects. The final analytical sample consists of 98,648 projects, including 97,054 extramural projects and 1,594 intramural projects, which produced 621,138 papers during our time window.

Cost effectiveness

We used the primary project costs listed on NIH RePORTER as the cost data source. Subproject costs were not calculated. Given the influence of price changes and inflations over years, we converted all funding costs at the 2015 price level using NIH's Biomedical Research and Development Price Index.

We used five paper-level metrics to measure the research output: number of papers; relative citation ratio (Hutchins et al., 2017; Hutchins et al., 2016); approximate potential to translate (Hutchins et al., 2019b; Santangelo, 2017; Weber, 2013); total clinical citation counts (Hutchins, 2021; Hutchins et al., 2019a; iCite et al., 2019); and number of papers once received clinical citations. A project's total research performance regarding a certain metric in one year is approximated as the sum of that metric for every paper published in that year.

Based on the project costs and research outputs, we calculated the cost per output as follows.

$$R_{ij} = \frac{C_{ij}}{O_{ij}} * \frac{P_{ij}}{TP_i}$$

Where R_{ij} is the cost per output for project i in year j, C_{ij} the cumulative sum of funding costs for project i up to year j, O_{ij} is the cumulative sum of a certain research performance metric for project i up to year j, P_{ij} is the cumulative number of papers for project i up to year j, and TP_i is the total number of papers for project i until 2020.

Regression analysis

We run the following regression model at the project level to estimate the differences between extra- and intramural projects for every year after the projects started.

$$\log(y_{it} + 1) = \beta_0 + \beta_1 I_i + \beta_2 T_t + \sum \beta p_i + \alpha\, r_t + \delta s_i$$

where y_{it} is project i's deflated cost efficiency regarding a certain research performance t years after the funding start year; I_i is whether project i is an intramural project (1 if yes); T_t is the length of funding years until that time point, equal to the minimum of t and the total funding years; p_i stands for the PI-related variables; r_t and s_i are the year's and project topic's fixed effects. We transformed the y_{it} into $\log(y_{it} + 1)$ to mitigate the impact of uneven distribution.

PI-related variables include the number of past publications, number of past projects, number of PIs, share of clinical papers, past publications' average relative citation ratio, publication experience, project experience, number of collaborators. We downloaded the PubMed Knowledge Graph datasets (Xu et al., 2020) to help extract the PI level variables. The dataset has disambiguated the authors of PubMed indexed publications and assigned unique identifiers to the authors. We matched both project numbers and paper author names with the datasets to find the PI's assigned unique identifiers. We successfully

retrieved the PI information for 98803 (94.9%) projects. The PI-related variables before the project funding started were extracted for every project, which played the proxy role of the input for the projects.

Another control variable, project topic, is calculated by performing a K-means clustering based on the NIH spending categories for all the projects in the sample. To restrict the dimensionality, the 100 most frequent NIH spending categories were used in clustering, which cover 96.4% of all projects. We tried k=3, 4…10 and finally selected k=5 which generated the highest silhouette score.

As a robustness check, we used propensity score matching to reduce the potential confounding biases that may affect the outputs of interest and increase the comparability between intramural and extramural projects. For every year after the projects started, we used all project-level variables, including the length of funding years until that time point, PI-related variables, and project topics, to predict the propensity score of each project by fitting a logistic regression model. The propensity score shows the probability of a project to be an intramural project, based on the observable variables. For each intramural project, we selected one and four extramural projects, respectively, with the nearest propensity scores from a pool of extramural projects with the same funding start year. The regression model was run on the PSM sample again to check the robustness of previous results.

Paper features

We used the concatenated documents of a paper's title and abstract to train a word2vec model (NIA OPA, 2018; NIH OPA, 2019) to classify the papers into clusters. We removed common stop words, punctuation, and content lacking semantic information before training. During clustering, each paper's document is represented as a 300-dimension vector by summing its each unique word's vector weighted by its IDF. Principal component analysis (PCA) dimensionality reduction is applied to these 300-dimensional vectors to identify the 25 most influential components. We finally performed spectral clustering method using the document vectors and extract highly-frequent words to determine the cluster property and labels. Word2Vec nearest neighbor terms were uploaded to ChatGPT to develop more human-readable labels.

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Supplemental Materials

Supplemental Text

Questions about the most effective approaches to structure portfolio management for science funders have been a source of contention. This is primarily due to the conflicting priorities among government officials, the mission of funding agencies, and the perspectives of scientific researchers (Goldstein & Kearney, 2020). While the 2018 Evidence Act (Abraham & Haskins, 2017; Young, 2021) mandates that all science funders incorporate data-driven decision-making, the U.S. Congress played a significant role in catalyzing such efforts, particularly at the National Institutes of Health (NIH), through the establishment of divisions such as the Office of Portfolio Analysis in 2011 (Department, 2011). The division was created to advance these data-driven initiatives even before they were broadly implemented across other federal agencies. Consequently, NIH serves as an excellent case study for policy examination, given its more extensive and robust data infrastructure compared to other agencies.

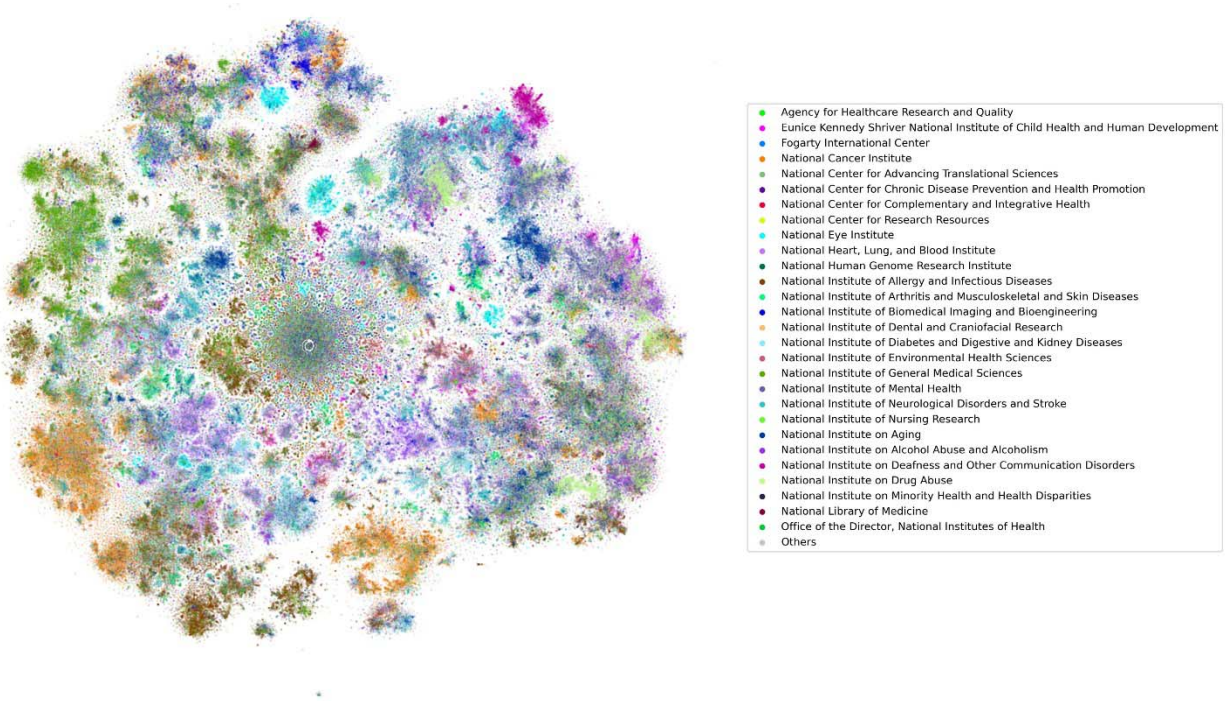
A pressing question that often surfaces, particularly when facing inflation-adjusted budgetary declines, concerns the comparative efficiency of externally funded grants, usually awarded to universities, medical institutions, and research centers, in contrast to intramurally funded projects where scientists are employed directly as government personnel and conduct research within federal facilities. The 2013 sequester (Fox, 2013), a budget reduction mechanism that abruptly removed a sizeable fraction of government funding for scientific research, revealed significant contention in the scientific community about the extent to which extramural versus intramural funding should shoulder the burden of budgetary declines (Scientopia, 2014).

Various theories exist to highlight the respective merits of these two funding models. Extramural institutions are thought to engage in extensive cost-sharing that might reduce the degree of government investment necessary to stimulate scientific advancement (Culliton, 1992; Korn, 2015; Macilwain, 1999). In effect, despite the negotiated indirect costs that are paid to offset institutional overhead that supports scientific research at extramural institutions, these institutions often contribute additional resources that foster science advance. Research indicates that institutional contributions, particularly in terms of trainee labor (Zhang, Wapman, Larremore, & Clauset, 2022), are important for stimulating scientific productivity, supporting this theory. Moreover, it is essential to recognize the substantial portion of extramural funding typically dedicated to training students and early career researchers. This investment not only aids in producing the next generation of researchers in the field but also contributes to the long-term sustainability of the research workforce (Harris, 2014). On the other hand, the direct hiring of scientists by the government under the intramural funding model allows for the selection of researchers whose research agendas more closely align with the agency's mission. Furthermore, despite shouldering the entire cost of intramural research, intramural PIs are freed from the time and resource burdens associated with grant applications. This freedom allows them to focus entirely on advancing scientific

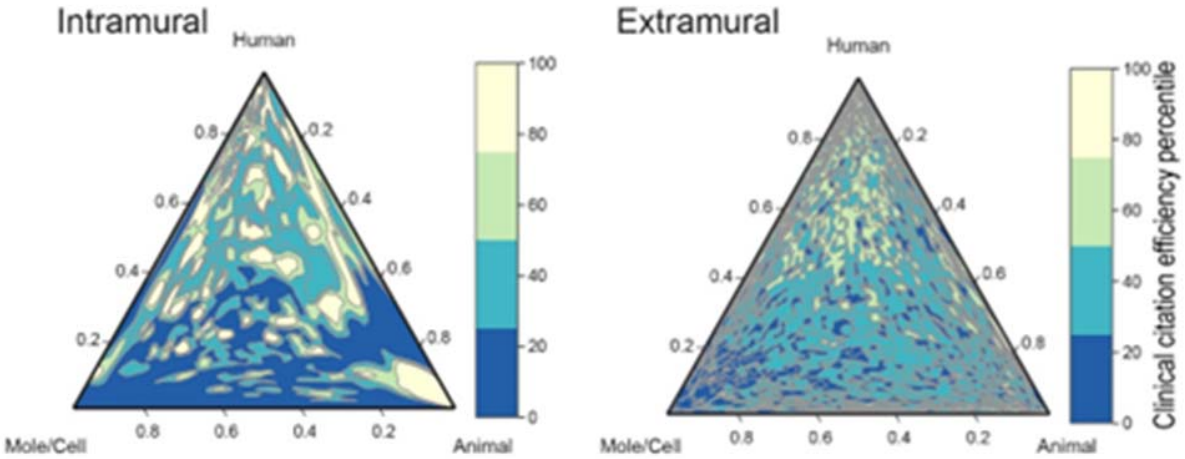
knowledge in their respective fields. Nonetheless, intramural grants may encounter constraints on autonomy due to their affiliation with a larger government institution, potentially restricting their freedom through manuscript clearance processes. This affiliation also implies that intramural researchers may not be entirely shielded from potential bureaucratic hurdles and unwarranted administrative burdens that can impede the progression of scientific endeavors. Therefore, each funding approach has unique strengths and considerations, making it essential to carefully weigh the advantages and disadvantages of extramural and intramural funding when allocating resources for scientific research.

Supplemental Figures

Supplemental Figure 1. T-SNE plot illustrating the distribution of topic clusters, with colors consistent with those in Figure 1. This shows a dimensionality reduction of the locations of these grants in Word2Vec space, indicating their relative proximity to one another. Grants with similar semantic meaning appear closer to one another, while those with less semantic similarity will appear farther away. Similar grants tend to cluster together in T-SNE visualizations.



Supplemental Figure 2. T-SNE plot illustrating the distribution of grants in NIH institutes, using the same methodology as Supplemental Figure 1. This shows a dimensionality reduction of the locations of these grants in Word2Vec space, indicating their relative proximity to one another. Grants with similar semantic meaning appear closer to one another, while those with less semantic similarity will appear farther away. Similar grants tend to cluster together in T-SNE visualizations.



Supplemental Figure 3. Ternary contour plots representing the clinical citation efficiency in the human, animal, and molecular/cellular score system for intramural (D) and extramural projects (E). (Hutchins, Davis, Meseroll, & Santangelo, 2019; Weber, 2013). Here, efficiency was the percentile of the cost per

output in descending order. Each contour line denotes a constant efficiency percentile. Yellow/green are high-efficiency areas of the triangle, and blues are low-efficiency areas.

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