Allocative Efficiency of Public R&D: Evidence from NIH Funding

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Abstract

This paper studies the allocative efficiency of public R&D funding using detailed data on NIH grants. We develop a framework in which heterogeneous research recipients transform public funds into knowledge and innovation outputs, measured by scientific publications and patents. The model highlights how distortions in funding allocation – captured as wedges between marginal products and marginal costs – affect aggregate research productivity. We estimate knowledge and innovation production functions exploiting panel variation in funding and introduce a novel identification strategy based on shifts in the composition of congressional committees and using dynamic panel data methods. Combining these estimates with administrative data linking grants to publications and patents, we recover recipient-level productivity and quantify misallocation across research areas. Our results show substantial heterogeneity in returns to funding across fields and recipients. Misallocation in knowledge production is economically large, with aggregate productivity losses ranging from roughly 10% to 85% relative to an efficient benchmark, while misallocation in innovation (patents) is more limited due to lower returns to scale. These findings imply that reallocating existing funds could generate sizable gains in scientific output without increasing total spending.

Keywords: Public R&D funding; misallocation; distortions; patents.
JEL classification: H51, L31, O31, O32, O38.

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Contents

1 Introduction **2**

2 Knowledge Production and Misallocation **2**

2.1 Knowledge production 2

2.2 Allocation of public funds within a research area 4

3 Measuring Misallocation **7**

3.1 Institutional Background 7

3.2 Award Data 8

3.3 Outcomes: Research Papers and Patents 12

4 Estimating the knowledge and innovation production functions **15**

4.1 Novel identification and estimation 15

4.2 Heterogeneity across research areas 15

4.3 Results: Estimates of the knowledge production function (papers) 17

4.4 Results: Estimates of the innovation production function (patents) 18

5 Quantifying misallocation **20**

5.1 Distributions of wedges, patterns and misallocation 20

5.2 Overheads 21

5.3 Discussion and Counterfactual 21

6 Conclusion and Outlook **21**

A Estimation of award-level production function **23**

1 Introduction

Literature

2 Knowledge Production and Misallocation

2.1 Knowledge production

We consider a model in which the government gives research awards to various recipients. Since we will study how effectively each recipient turns public awards into research output, we will focus on heterogeneity across recipients. Public research funds are turned into three kinds of output: First, general knowledge, which we will approximate by research papers. Second, direct patents, i.e. patents that directly cite a research award. Third, indirect patents, which cite research papers generated with public funding.

Let G_{ist} denote the dollar amount of government research funds awarded to recipient i to do research in field s in year t. These funds are possibly given through several awards, which we sum up to the recipient-research area-year level for the purposes of this analysis. This implicitly assumes that research awards to a given recipient are perfectly substitutable and only the total dollar amount matters for research outcomes. In the appendix, we also consider an analysis at the level of the individual research award.

A recipient turns these resources into one of the three above mentioned outcomes $Y_{ist} \in \{\text{Papers}_{ist}, \text{Patents}_{ist}, ...\}$ using the following "production function"

$$\begin{aligned} Y_{ist} &= A_{ist} G_{ist}^{\beta_s} \\ y_{ist} &= a_{ist} + \beta_s g_{ist} \end{aligned} \tag{1}$$

where lower case letters denote the logarithm of variables denoted by upper case letters. The time subscript warrants some explanation. Research funds G_{ist} are awarded in a given year t, but may be obligated over many years thereafter. The research output, Y_{ist}, is therefore *not* the research output in a particular year t. Rather, it is the research output *generated with resources awarded in year t* even if they occur many years later. This interpretation is the proper link between inputs (research funds) and outputs (research products) and made possible by the fact that outputs explicitly have to cite their particular government award source, be it that they occur immediately or several years after the award.

The general elasticity of research output with respect to funds, β_s, is assumed to be the same across recipients engaged in the same type of research, but it may differ across research areas s. Recipients engaged in similar research differ, however, in their general research productivity A_{ist}. This means we can study the allocation of resources across heterogeneous recipients within a research area. Because we will be silent on resources allocation across research areas, we will from now on omit the subscript s as it is understood we study only the within-area allocation.

We want to remind the reader that research outputs come in different forms. First, resources spent on research activities generate new knowledge as measured by research papers and books. Then, equation (1) reflects a knowledge production function with a particular knowledge production elasticity β and a distribution of knowledge production productivities $\{A_{it}\}$, one for each recipient awarded resources in a given time and research area. We will later also consider a variant of the knowledge production function where the left hand side variable is weighted by the quality of the journal publishing the new knowledge output. Then, this will be a quality adjusted knowledge production function.

Next, we will consider the patents that are generated with public research funds. Patent filings have to explain the nature of their innovation and the knowledge underlying the innovation. As illustrated in Figure 1, patents may emerge directly from a publicly funded research project (along with research papers and other knowledge products); we call these "direct patents." But often, research that is funded by the government amounts to basic research, which is not directly

patentable. For example, basic research that discovered T-cell activation and immune checkpoints led to immunotherapy in cancer treatment. Only the latter is the patented innovation, which build on the government funded research from decades earlier. Because the government funds directly generated only knowledge, which are the basis for a later patent, we call these "indirect patents". In the NIH data, the mapping from government funded research to later patents is well documented and they reflect of about 90% of all patents that are ever linked to a government research award.

If we put patents on the left hand side of equation (1), we consider an "innovation production function" that reflects the mapping from government research funds to knowledge creation to innovation. As above, we can also weigh the patents on the left hand side variable by the quality of the patent as measured by its citations or disruptiveness.

To summarize, we will have different sets of $(\beta, \{A_{it}\})$, one for each output variable on the left hand side: research papers, quality weighted research papers, patents and quality weighted patents. We will now proceed to developing a simple framework on the allocation of government resources to heterogeneous recipients in a given research area.

2.2 Allocation of public funds within a research area

Aggregate knowledge production In a given year, the government has to allocate its total research budget across the individual recipients i and programs s. We focus on the allocation of a research budget within a research area because taking a stand on the relative importance between entire research areas is difficult. How does one trade off research output in cancer research versus immunology for instance? Discriminating across agents of research activity within a given research area, however, seems much more sensible. From now on, we only consider the within-area research funding problem.

We assume the government tries to maximize research output Y_t subject to the total amount of research funding going, G_t. Its task is to allocate that pie optimally across recipients with heterogeneous research ability A_{it} by choosing an allocation G_{it}.

Aggregate research output in area is just the sum of all research output from each recipient in that area:

$$Y_t = \sum_i Y_{it} = \sum_i A_{it} G_{it}^{\beta}.$$

This functional form implies that research output of individual grants and recipients are perfect substitutes. This means it does not matter who or what grant produces a particular paper or patent. Given that all recipients operate the same technology (same β) and differ only in their "total research productivity" A_{it}, this seems plausible. The declining returns to scale in research production also imply that it can be efficient to allocate funds to recipients or grant proposals with a lower productivity A_{it}.

The government's problem In principle, the government aims at allocating funds in a way that maximizes expected research output, which implies that the marginal product of research across recipients should be equalized and equal to the marginal cost of public funds, denoted by λ_t.

But the process of screening, evaluating and awarding public resources is likely an imperfect activity. This imperfection is captured by a distortion to the marginal costs of public funds, which we denote by τ_{it}, so the effective marginal cost of a dollar for each project is $\lambda_t(1+\tau_{it})$. The government's first-order condition for each recipient becomes:

$$\beta A_{it} G_{it}^{\beta-1} = \lambda_t(1+\tau_{it}) \qquad \forall i. \tag{2}$$

If $\tau_{it} > 0$, then the recipient project receives too little funding for its awards compared to the optimal undistorted allocation.

We can infer the distribution of these τ_{it} for each pair of recipients (i,k) as follows:

$$\frac{\beta A_{it} G_{it}^{\beta-1}}{\beta A_{kt} G_{kt}^{\beta-1}} = \frac{1+\tau_{it}}{1+\tau_{kt}} \qquad \forall j \neq k \tag{3}$$

Note: we can use the ratio of any two pairs to get at the τ's. It will be useful to express a recipient's funding as a function of funding to a reference recipient:

$$G_{it} = \left(\frac{1+\tau_{kt}}{1+\tau_{it}}\frac{A_{it}}{A_{kt}}\right)^{\frac{1}{1-\beta}} G_{kt}$$

Using that information, we can sum up over all recipients to get the total amount of public funds in research area as follows:

$$\begin{aligned} G_t &= \sum_i G_{it} \\ &= \sum_i \left[\frac{1+\tau_{kt}}{1+\tau_{it}}\frac{A_{it}}{A_{kt}}\right]^{\frac{1}{1-\beta}} G_{kt} \\ &= \left(\frac{1+\tau_{kt}}{A_{kt}}\right)^{\frac{1}{1-\beta}} G_{kt} \sum_{it} \left(\frac{A_{it}}{1+\tau_{it}}\right)^{\frac{1}{1-\beta}} \end{aligned}$$

Note that $\left(\frac{1+\tau_{kt}}{A_{kt}}\right)^{\frac{1}{1-\beta}} G_{kt}$ is the same for all i,k because it equals $\left(\frac{\beta}{\lambda_t}\right)^{\frac{1}{1-\beta}}$. Behold also that the share of each grant's funding in research area funds G_t can be expressed as follows:

$$\frac{G_{it}}{G_t} = \frac{\left(\frac{A_{it}}{1+\tau_{it}}\right)^{\frac{1}{1-\beta}}}{\sum_i \left(\frac{A_{it}}{1+\tau_{it}}\right)^{\frac{1}{1-\beta}}} \tag{4}$$

The higher a recipient's productivity, the higher its funds, but higher distortions will diminish its

share in the pie. The higher the production elasticity β, the worse the effect of these distortions on the distribution of funds.

Aggregating research output We can now express how much research output in area s declines due to distortions across recipients. Starting from the research area production function and utilizing equations (1) and (4), we get:

$$\begin{aligned}
Y_t &= \sum_i Y_{it} = \sum_i A_{it} G_{it}^{\beta} \\
&= \sum_i A_{it} \left(\frac{G_{it}}{G_t} \right)^{\beta} G_t^{\beta} \\
&= \underbrace{\frac{\sum_i \left(\frac{A_{it}}{(1+\tau_{it})^{\beta}} \right)^{\frac{1}{1-\beta}}}{\left[\sum_i \left(\frac{A_{it}}{1+\tau_{it}} \right)^{\frac{1}{1-\beta}} \right]^{\beta}}}_{\equiv A_t} G_t^{\beta} \\
Y_t &= A_t G_t^{\beta}
\end{aligned}$$

Note how the aggregate research productivity, denoted by A_t, depends on both the distribution of innate scientific abilities, A_{it}, as well as the distortions τ_{it}.

Distortions and aggregate efficiency of research funding We can now get an idea about the misallocation in a particular research area, which can be expressed by how much A varies with the distortions τs. Let A_t^{eff} be the research productivity in the absence of distortions and $\mathcal{E}_t$ denote how close the allocation gets to the efficient one. Then we can write:

$$\begin{aligned}
\mathcal{E}_t &= \frac{A_t}{A_t^{eff}} \\
&= \frac{\sum_i \left(\frac{A_{it}}{(1+\tau_{it})^{\beta}} \right)^{\frac{1}{1-\beta}} \Big/ \left[\sum_i \left(\frac{A_{it}}{1+\tau_{it}} \right)^{\frac{1}{1-\beta}} \right]^{\beta}}{\sum_i A_{it}^{\frac{1}{1-\beta}} \Big/ \left[\sum_{it} A_{it}^{\frac{1}{1-\beta}} \right]^{\beta}} \\
&= \frac{\sum_i \left(\frac{A_{it}}{(1+\tau_{it})^{\beta}} \right)^{\frac{1}{1-\beta}}}{\left[\sum_i \left(\frac{A_{it}}{1+\tau_{it}} \right)^{\frac{1}{1-\beta}} \right]^{\beta} \left[\sum_i A_{it}^{\frac{1}{1-\beta}} \right]^{1-\beta}}
\end{aligned} \tag{5}$$

This measure varies between zero (very bad misallocation) to one (no misallocation at all).

3 Measuring Misallocation

3.1 Institutional Background

We focus on research grants awarded by the National Institutes of Health (NIH), one of the largest public funders of R&D in the United States. In fiscal year 2023, the NIH awarded more than 50 billion USD in research funding, making it the second-largest federal R&D agency after the Department of Defense . Given both its scale and its central role in financing biomedical research, the NIH represents a quantitatively and substantively important setting for studying the allocation and consequences of public R&D funding.

Beyond its size, the NIH provides an unusually rich and transparent administrative data infrastructure. Through the NIH RePORTER platform, detailed information is publicly available on funded grants, including award amounts, principal investigators, institutional affiliations, funding institutes, project abstracts, and funding histories. Importantly, the NIH systematically links grants to resulting scientific publications via PubMed identifiers. Moreover, patents can be matched to NIH-funded research with reasonably high accuracy, mainly through OpenAlex. These data combined allow for a granular tracing of knowledge production from funding allocation to downstream scientific and technological outputs.

The NIH is composed of multiple institutes and centers, each dedicated to specific disease areas or scientific domains – for example, cancer (NCI), aging (NIA), heart, lung and blood diseases (NHLBI), neurological disorders (NINDS), and many others. While funding decisions are decentralized across institutes, all operate under a common institutional framework and evaluation procedure. This structure creates meaningful variation in funding allocations across scientific areas while maintaining comparability in review processes.

NIH awards process is competitive and investigator-initiated. Researchers affiliated with universities, independent research institutes, medical centers, and in some cases private firms submit detailed grant proposals outlining scientific objectives, methodology, expected contributions, and budgets. Proposals undergo peer review based on scientific merit, feasibility, and potential impact. Funding decisions are made following this evaluation process, subject to institute-level priorities and budget constraints.

Crucially for empirical analysis, the NIH publicly discloses all awarded grants and systematically documents associated research outputs. As illustrated in Figure1, innovation stemming from NIH funding can be conceptualized along two channels. First, patents may arise directly from a funded project, which is defined as a patent that explicitly acknowledges NIH funding grant in the patent application. We refer to these as "Direct Patents." Second, innovation may occur more indirectly, potentially many years later, when a patent cites a scientific publication that was generated with NIH support. We refer to such downstream technological developments as "Indirect Patents." Distinguishing between these channels allows us to capture both the immediate and the longer-run, knowledge-mediated effects of public research funding.

3.2 Award Data

In the following, we present summary statistics for the NIH award data. Our baseline sample focuses on awards made between 1985 and 2020. We exclude pre-1985 grants because the number of recorded awards exhibits a discrete drop prior to that year, raising concerns about data completeness and comparability. We also exclude post-2020 awards, as these grants are unlikely to have generated observable patent outcomes within our sample window.[1] This restriction ensures that funded projects have had sufficient time to produce measurable innovation outputs. We compute summary statistics for grants within a given institute and year and then average across years by institute, to obtain statistics for the average year.

As shown in Table 1, the median NIH grant in our sample amounts to 530 thousand USD. However, the distribution of award sizes is highly dispersed. The interquartile range exceeds 1.5 million USD, indicating substantial heterogeneity between the lower and upper quartiles. In addition, the distribution is markedly right-skewed, reflecting the presence of a small number of exceptionally large ("jumbo") awards. The Kelley skewness coefficient of 0.7 underscores this asymmetry: the distance between the 90th percentile and the median is nearly six times (=(1+0.7)/(1-0.7)) as large as the distance between the median and the 10th percentile. One exception is NIBIB, which does not award smaller grants and therefore has a lower skewness.

There is also pronounced heterogeneity across institutes, consistent with differences in disease focus, research intensity, and funding priorities. For example, the median award in the National Institute of Nursing Research is less than a quarter than the median award given b the National Institute of Biomedical Imaging and Bioengineering. This cross-institute variation provides an additional dimension of heterogeneity that is central to our empirical analysis.

[1] The average time from grant award to patent filing is X years, while the average time from patent application to patent approval is Y years.

Figure 1: The research process and its outcomes

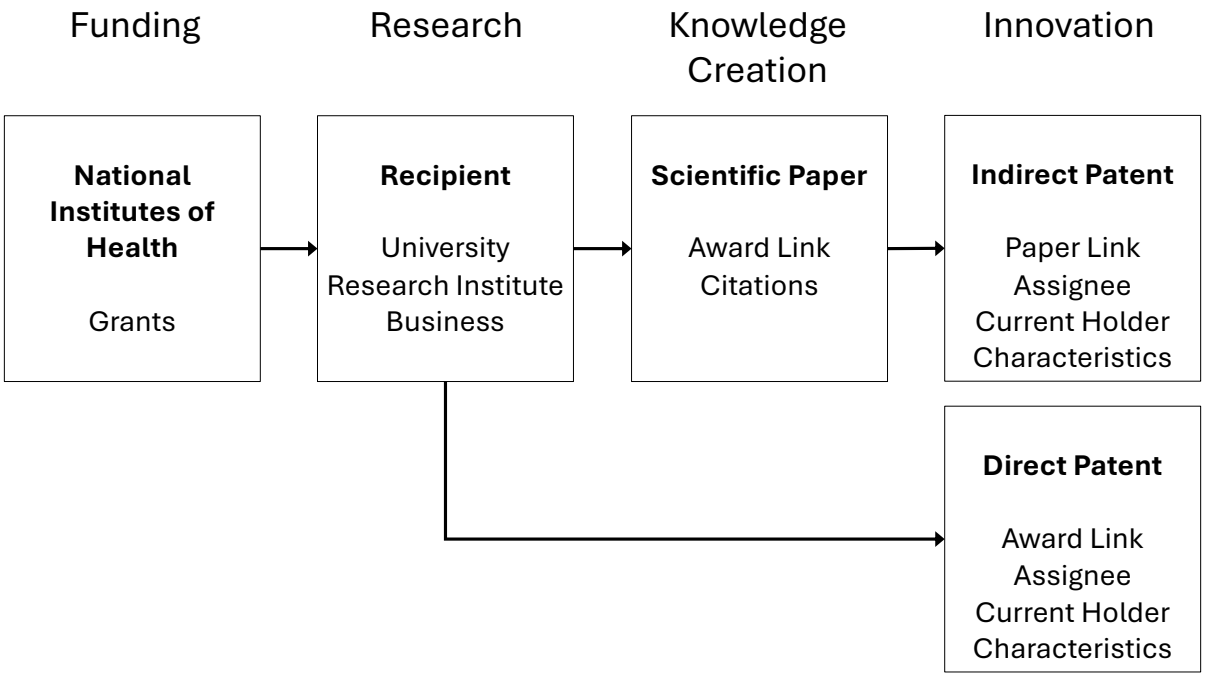


Table 1: Summary Statistics of NIH Grants – Total costs (in thousand USD)

Institute	Mean	P25	P50	P75	Kelley Skewness	CR4	CR20	N
Aging	1,881	179	596	1,716	.72	20	43	1,429
Alcohol Abuse	1,360	215	597	1,672	.66	18	44	364
Allergy	2,154	280	637	1,955	.75	14	30	1,953
Arthritis	1,242	186	563	1,486	.67	14	39	920
Biomedical	1,869	507	1,234	2,588	.53	40	65	343
Cancer	1,861	187	721	1,659	.61	15	28	1,951
Child Health	1,444	152	537	1,534	.72	15	33	859
Deafness	1,381	157	473	1,661	.78	17	49	312
Dental	1,162	152	429	1,353	.76	19	49	294
Diabetes	1,524	193	737	1,652	.6	11	25	1,032
Drug Abuse	1,700	220	740	2,056	.65	14	34	828
Env Health	1,887	157	584	1,709	.71	27	54	321
Eye	1,565	222	736	1,770	.64	14	38	422
General Medical	1,519	164	767	1,585	.55	7.5	21	1,425
Heart, Lung, and Blood	1,862	282	994	1,982	.51	8.9	23	1,724
Human Genome	3,163	313	865	2,086	.71	47	78	157
Mental Health	1,328	184	606	1,554	.65	10	25	1,013
Neurological Disease	1,369	170	626	1,546	.65	9.4	24	1,352
Nursing Research	831	109	281	1,258	.8	20	59	164
Total	1,651	180	664	1,660	.66	4.7	10	15,203

Note: Summary statistics of a pooled panel of NIH grants 1985-2020. Mean denotes the average grant size, P25, P50 and P75 denote the according percentile across awards, the Kelley Skewness is defined as [(P90-P50)-(P50-P10)]/(P90-P10). CR4 and CR20 are the share of obligations going to the four and twenty largest awards, respectively.

Table 2: Summary Statistics of NIH Grant Recipients – Total costs (in thousand USD)

Institute	Mean	P25	P50	P75	Kelley Skewness	CR4	CR20	No. of Recipients	No. of grants per recipient	
									average	median
Aging	5,178	263	1,243	4,294	.81	29	66	289	2.85	1.36
Alcohol Abuse	2,702	359	1,180	3,246	.66	27	64	133	2.04	1.22
Allergy	8,020	285	1,474	5,946	.86	25	56	385	3.78	1.82
Arthritis	2,917	218	1,107	3,362	.75	25	65	182	2.42	1.22
Biomedical	2,715	598	1,602	3,406	.56	48	79	150	1.69	1.03
Cancer	7,541	189	1,098	4,873	.89	25	55	434	4.09	1.17
Child Health	3,917	226	1,079	3,794	.81	22	56	272	2.75	1.38
Deafness	2,601	289	1,091	3,294	.7	26	67	140	2.01	1.21
Dental	2,724	229	1,053	3,219	.74	30	74	118	2.37	1.26
Diabetes	5,747	260	1,358	5,469	.84	23	58	243	3.81	1.75
Drug Abuse	4,117	388	1,522	4,413	.73	22	56	261	2.5	1.29
Env Health	3,387	264	1,032	3,130	.74	33	70	161	1.85	1.04
Eye	3,633	326	1,349	4,374	.73	26	64	143	2.35	1.33
General Medical	5,234	259	1,257	5,396	.85	16	46	378	3.45	1.65
Heart, Lung, and Blood	7,751	255	1,441	6,538	.88	21	55	354	4.18	1.64
Human Genome	5,063	477	1,221	3,191	.78	59	90	82	1.62	1.03
Mental Health	4,899	378	1,431	4,462	.8	23	58	236	3.67	1.81
Neurological Disease	5,168	292	1,438	5,359	.81	21	55	257	3.85	1.83
Nursing Research	1,664	246	892	2,182	.63	33	79	77	2.04	1.17
Total	5,236	246	1,214	4,319	.83	6.7	16	3,819	3.2	1.06

Next, we provide summary statistics at the level of the recipient. To that end, we sum all grants and their characteristics by recipient. Statistics here will tell how many resources individual recipients (universities) receive across grants. As Table 2 shows, institutions receive on average 3.2 grants per year though this is heavily right skewed as the median recipient receives only 1 grant. The median recipient receives about 1 million USD again with significant dispersion and right-skewness, both of which are more pronounced than at the award-level. This means recipients of several grants tend to get more funding per award than recipients with fewer awards per year and institute.

Interestingly, at the the recipient level, the median recipient across institutes receives much more similar amounts than at the grant level.

3.3 Outcomes: Research Papers and Patents

Table 3: Summary Statistics of NIH Grants – Cost (in 1,000$), Papers per 1mn$ and Patents per 1mn$

Institute	Mean			Median			Kelley Skewness		
	Cost	Papers	Patents	Cost	Papers	Patents	Cost	Papers	Patents
Aging	1,881	6.1	.73	596	2.7	.000022	.72	.63	1
Alcohol Abuse	1,360	6.8	.22	597	2.8	0	.66	.64	1
Allergy	2,154	71	9.5	637	2.1	.07	.75	.59	.95
Arthritis	1,242	6.4	1.4	563	3	.035	.67	.59	.97
Biomedical	1,869	6.4	2	1,234	4.1	.57	.53	.41	.76
Cancer	1,861	5.2	1.6	721	2.2	.018	.61	.62	.98
Child Health	1,444	52	.49	537	2.4	0	.72	.67	1
Deafness	1,381	6	.64	473	2.9	0	.78	.61	1
Dental	1,162	6.3	.94	429	2.6	.0017	.76	.63	1
Diabetes	1,524	30	.84	737	2.8	.028	.6	.58	.97
Drug Abuse	1,700	5.7	.47	740	2.2	0	.65	.7	1
Env Health	1,887	8.6	.8	584	2.1	0	.71	.68	1
Eye	1,565	12	1	736	2.2	.0064	.64	.61	.99
General Medical	1,519	5.8	1.8	767	3	.0071	.55	.55	.99
Heart, Lung, and Blood	1,862	5.5	.93	994	2.5	.017	.51	.59	.98
Human Genome	3,163	4.2	2.6	865	1.4	.053	.71	.72	.95
Mental Health	1,328	7.6	.86	606	2.5	0	.65	.73	1
Neurological Disease	1,369	10	.8	626	2.8	.0088	.65	.55	.99
Nursing Research	831	11	.38	281	3.4	0	.8	.78	1
Total	1,651	18	1.9	664	2.5	.00021	.66	.63	1

Table 4: Summary Statistics of NIH Grant Recipients – Cost (in 1,000$), Papers per 1mn$ and Patents per 1mn$

Institute	Mean			Median			Kelley Skewness		
	Cost	Papers	Patents	Cost	Papers	Patents	Cost	Papers	Patents
Aging	5,178	5.2	.41	1,243	2.8	.012	.81	.52	.97
Alcohol Abuse	2,702	5.9	.18	1,180	2.8	0	.66	.52	1
Allergy	8,020	3.7	.84	1,474	1.9	.087	.86	.52	.91
Arthritis	2,917	6.1	1.3	1,107	3.3	.095	.75	.45	.92
Biomedical	2,715	6.3	1.7	1,602	4.1	.68	.56	.37	.7
Cancer	7,541	3.5	1.1	1,098	1.5	.015	.89	.64	.99
Child Health	3,917	126	.36	1,079	2.5	.00027	.81	.56	1
Deafness	2,601	5	.39	1,091	3	.0012	.7	.45	1
Dental	2,724	5.4	1.2	1,053	2.9	.021	.74	.49	.97
Diabetes	5,747	4.4	.72	1,358	2.7	.061	.84	.42	.91
Drug Abuse	4,117	4.7	.39	1,522	2.3	.0017	.73	.6	1
Env Health	3,387	10	.96	1,032	2.3	.00039	.74	.59	1
Eye	3,633	4.2	.63	1,349	2.5	.036	.73	.44	.95
General Medical	5,234	4.8	1.3	1,257	3.3	.071	.85	.38	.94
Heart, Lung, and Blood	7,751	4.2	.85	1,441	2.2	.037	.88	.46	.95
Human Genome	5,063	3.8	2	1,221	1.4	.087	.78	.69	.97
Mental Health	4,899	5.5	.29	1,431	2.6	.00012	.8	.55	1
Neurological Disease	5,168	4.6	.57	1,438	2.9	.048	.81	.37	.91
Nursing Research	1,664	7.5	.3	892	3.4	0	.63	.61	1
Total	5,236	13	.8	1,214	2.5	.0044	.83	.51	.99

4 Estimating the knowledge and innovation production functions

4.1 Novel identification and estimation

- we have to confront a standard identification problem of the production function literature
- our approach: ways and means committee is composed of representatives from 435 districts; we construct a "research profile" for each district. That is how much funding of a NIH research area typically went to recipients located in a paricular district.
- then we look at committee changes, which leads to changes in the research profile represented on the committee, which is our instrument for allocating funds to different NIH research areas.
- pro: new, credible, exogenous
- con: lacks power for individual research areas, but good enough for an aggregate
- do aggregate estimation, compare to AB, compare to literature

4.2 Heterogeneity across research areas

OLS

FE Nickell (1981) bias

Arellano-Bond We are interested in assessing the aggregate effects of reallocation of funding across recipients in a given research area. This will depend on the returns to scale, β, and the distribution of A_{it}. Like the traditional production function estimation literature, we have to confront the obvious endogeneity problems.[2] For now we do that using the dynamic panel data methods developed by Arellano and Bond (1991). First, we make further assumptions about the nature of research productivity of individual recipients i. We assume each recipient's research productivity (in logarithms) is characterized by a permanent component (denoted by a_i) and a transitory component (denoted by b_{it}) where the latter follows an autoregressive process. Letting lower case letters denote logarithms of upper case letters, we have:

$$\begin{aligned} a_{it} &= a_i + b_{it} \\ &= a_i + \rho b_{it-1} + \eta_{it}. \end{aligned}$$

[2] We will have to confront the selection issue in our estimation of β

$$Y_{it} = \begin{cases} 0 & \text{if } A_{it} < A^* \\ Y_{it} & \text{if } A_{it} \geq A^*. \end{cases}$$

Check out the papers by Kyriazidou (2001); Semykina and Wooldridge (2010, 2013); Sasaki (2015); Baltagi et al. (forthcoming).

This means , we can rewrite our production function (in logs) as follows:

$$\begin{aligned} y_{it} &= a_{it} + \beta g_{it} \qquad (6) \\ &= a_i + b_{it} + \beta g_{it} \\ &= a_i + \rho b_{it-1} + \eta_{it} + \beta g_{it} \\ &= a_i + \rho \left[y_{it-1} - a_i - \beta g_{it-1} \right] + \eta_{it} + \beta g_{it} \\ &= (1-\rho) a_i + \rho y_{it-1} + \beta g_{it} - \beta \rho g_{it-1} + \eta_{it}. \qquad (7) \end{aligned}$$

To estimate β (and ρ), we instrument for the RHS variables using $\{\Delta y_{it-1}, \Delta g_{it-1}, \Delta g_{it-2}\}$ all of which are orthogonal to η_{it}.

Alternatively, we can estimate equation (7) in first differences:

$$\Delta y_{it} = \rho \Delta y_{it-1} + \beta \Delta g_{it} - \rho \beta \Delta g_{it-1} + \Delta \eta_{it}.$$

To maintain orthogonality with $\Delta \eta_{it}$, we choose $\{y_{it-2}, g_{it-2}, g_{it-3}\}$ as instruments.

With our estimate of β (and ρ and a_i?) at hand, we can use the production function (6) to back out the research productivity a_{it} and estimate the auto-regressive parameter ρ and the properties of η_{it}.

Appendix A contains an alternative estimation procedure.

This setup assumes that the government knows all components of a recipient's research productivity: $A_{it} = \exp\left[a_i + \rho b_{it-1} + \eta_{it}\right]$. We could also assume that the government does not know η_{it}; then we have to replace A_{it} below with $\tilde{A}_{it} = \exp\left[a_i + \rho b_{it-1}\right]$.

- do AB at research/disease area level, show how heterogneous they are and
- compute recipient FE across research areas and show how they are different

Implementation in data (already coded)

To quantify the efficiency loss, we proceed to get inference on the relevant parameters as follows:

1. β: we estimate this using AB.
2. A_{it}: calculate using the production function (1) with data on Y_{it} and G_{it}; if applicable, extract the forecastable component $\tilde{A}_{it} = \exp\left[a_i + \rho b_{it-1}\right]$; then the FOC will yield a forecastable distortion $\tilde{\tau}_{it}$.
3. generate aux$= \lambda_t(1+\tau_{it})$: from FOC (2); summarize that auxiliary variable
4. Get τ_{it} by dividing aux by its mean (in a given year and area) subtract 1
5. truncate those observations in the 1%-iles of the τ distribution; throw those observations away to get a "reasonable sample."

6. Feed the A_{it} and τ_{it} into equation (5).

4.3 Results: Estimates of the knowledge production function (papers)

- Show table with β and stats on A_{it} dispersion/skewness.

- How much do βs differ across research areas?
- Maybe table with total funding and total number of papers and patents by research area to get a feel for aggregate magnitudes.
- Give example of A_{it} dispersion.
- Summary and rankings of A_{it}, variance decomposition of a_i and b_{it} – How much variation comes form FE versus transitory effect?
- Rankings of a_i and/or A_{it}. Do a_i rank correlated across research areas?

Table 5: Misallocation Analysis: Asinh Papers

IC Name	$\hat{\beta}_{OLS}$	$\hat{\beta}_{FE}$	$\hat{\beta}_{AB1}$	$\hat{\beta}_{AB2}$	$\hat{\rho}_{AB1}$	$\hat{\rho}_{AB2}$	E_{OLS}	E_{FE}	E_{AB1}	E_{AB2}
Aging	0.6005	0.5820	0.5677	0.5552	-0.2279	-0.3831	0.7416	0.7551	0.7645	0.7720
Diabetes	0.6003	0.5306	0.5269	0.5060	-0.0896	-0.1711	0.7929	0.8283	0.8298	0.8379
Drug Abuse	0.4906	0.4729	0.5056	0.4839	-0.0829	-0.2457	0.8073	0.8155	0.7999	0.8105
Env Health	0.4550	0.5283	0.5769	0.5794	-0.1256	-0.2069	0.7914	0.7440	0.6983	0.6956
Eye	0.7053	0.5945	0.6424	0.6376	-0.2073	-0.2554	0.5512	0.7619	0.6923	0.7006
General Medical	0.7360	0.6440	0.7075	0.6732	-0.0932	-0.2981	0.6716	0.7833	0.7202	0.7599
Heart, Lung, and Blood	0.5995	0.4690	0.5394	0.5239	-0.1931	-0.3567	0.3041	0.6930	0.4937	0.5437
Human Genome	0.5229	0.4707	0.5779	0.5432	0.0795	-0.1225	0.5956	0.6335	0.5449	0.5786
Mental Health	0.5111	0.4870	0.5024	0.5001	-0.1364	-0.2611	0.8134	0.8268	0.8185	0.8197
Neurological Disease	0.5903	0.5475	0.5415	0.5315	-0.2510	-0.3850	0.8113	0.8398	0.8431	0.8481
Nursing Research	0.4240	0.4267	0.4400	0.4458	-0.0524	-0.2007	0.8515	0.8507	0.8467	0.8449
Alcohol Abuse	0.5321	0.5421	0.5214	0.5256	-0.2224	-0.3292	0.6978	0.6845	0.7113	0.7062
Allergy	0.4010	0.4095	0.4566	0.3968	0.0635	-0.1639	0.8149	0.8111	0.7887	0.8168
Arthritis	0.6286	0.5945	0.6606	0.6478	-0.2593	-0.3741	0.6941	0.7426	0.6329	0.6594
Biomedical	0.7211	0.6817	0.6437	0.6751	-0.1028	-0.2128	0.3790	0.4836	0.5801	0.5010
Cancer	0.4980	0.4170	0.6460	0.5892	-0.0807	-0.2776	0.7628	0.8287	0.4367	0.6027
Child Health	0.4663	0.4183	0.4200	0.4422	-0.1370	-0.2060	0.8227	0.8420	0.8413	0.8327
Deafness	0.6071	0.5877	0.6209	0.6367	-0.2163	-0.3423	0.7902	0.7988	0.7833	0.7747
Dental	0.5672	0.5303	0.5783	0.6006	-0.1688	-0.2213	0.7500	0.7767	0.7410	0.7208

Note: This table displays the estimated knowledge production function in equation (1) by research area where knowledge is defined the number of research papers. Then, we compute the estimated loss in aggregate research productivity implied by equation (5) given the estimated research productivities A_{it} and their associated distortions τ_{it}.

- Results show significant heterogeneity of the knowledge production function across research areas.
- Returns to scale quite decreasing in allergy diseases, while returns to scale are much higher in Eye

- The associated misallocation implied by the estimates are significant: They range from 10% to 85% from what is possible given the research frontier.

Table 6: Misallocation Analysis: Asinh Papers (JIF Weighted)

IC Name	$\hat{\beta}_{OLS}$	$\hat{\beta}_{FE}$	$\hat{\beta}_{AB1}$	$\hat{\beta}_{AB2}$	$\hat{\rho}_{AB1}$	$\hat{\rho}_{AB2}$	E_{OLS}	E_{FE}	E_{AB1}	E_{AB2}
Aging	0.7002	0.6466	0.6634	0.5938	-0.2129	-0.3687	0.7040	0.7528	0.7399	0.7836
Diabetes	0.7176	0.5819	0.5890	0.5501	-0.1016	-0.2215	0.7279	0.8226	0.8198	0.8340
Drug Abuse	0.5214	0.4915	0.5594	0.5172	-0.0129	-0.1839	0.7846	0.7997	0.7625	0.7869
Env Health	0.5227	0.5813	0.6265	0.6381	-0.1419	-0.2240	0.7594	0.7120	0.6587	0.6416
Eye	0.8247	0.6747	0.7460	0.7125	-0.1840	-0.2598	0.2244	0.5985	0.4116	0.5031
General Medical	0.8638	0.6988	0.7869	0.7260	-0.1750	-0.3366	0.3805	0.7389	0.6001	0.7100
Heart, Lung, and Blood	0.7141	0.5259	0.6036	0.5666	-0.1423	-0.3279	0.0988	0.5094	0.2861	0.3878
Human Genome	0.6832	0.5894	0.7562	0.7235	-0.0293	-0.2454	0.1922	0.3584	0.1095	0.1411
Mental Health	0.6033	0.5357	0.6045	0.5848	-0.1356	-0.2711	0.6700	0.7754	0.6675	0.7060
Neurological Disease	0.7198	0.6305	0.6296	0.6076	-0.2935	-0.4246	0.7376	0.8303	0.8308	0.8425
Nursing Research	0.4562	0.4475	0.4764	0.4820	-0.0679	-0.2286	0.8654	0.8673	0.8610	0.8598
Alcohol Abuse	0.5477	0.5476	0.5642	0.5160	-0.2148	-0.3484	0.7626	0.7627	0.7504	0.7830
Allergy	0.4992	0.4599	0.5538	0.4465	0.0741	-0.1747	0.7987	0.8130	0.7770	0.8177
Arthritis	0.7326	0.6646	0.7109	0.7026	-0.1901	-0.3755	0.4782	0.6216	0.5284	0.5467
Biomedical	0.7803	0.7040	0.6821	0.7205	-0.1532	-0.2787	0.2279	0.4028	0.4632	0.3592
Cancer	0.6042	0.4713	0.7004	0.6332	-0.0104	-0.2771	0.5870	0.7996	0.3010	0.5020
Child Health	0.5142	0.4346	0.4394	0.4959	-0.1061	-0.1982	0.8203	0.8473	0.8458	0.8270
Deafness	0.6666	0.6230	0.6142	0.6328	-0.2040	-0.3313	0.7989	0.8153	0.8181	0.8120
Dental	0.6442	0.5952	0.6903	0.7306	-0.1665	-0.2450	0.6860	0.7391	0.6137	0.5279

Note: This table displays the estimated knowledge production function in equation (1) by research area where knowledge is defined as the number of research papers weighted by their citations and the impact factor of the journal they appeared in. Then, we compute the estimated loss in aggregate research productivity implied by equation (5) given the estimated research productivities A_{it} and their associated distortions τ_{it}.

4.4 Results: Estimates of the innovation production function (patents)

- Show table with β and stats on A_{it} dispersion/skewness.

- How much do βs differ across research areas?
- Maybe table with total funding and total number of papers and patents by research area to get a feel for aggregate magnitudes.
- Give example of A_{it} dispersion.
- Summary and rankings of A_{it}, variance decomposition of a_i and b_{it} – How much variation comes form FE versus transitory effect?
- Rankings of a_i and/or A_{it}. Do a_i rank correlated across research areas?
- Results are a bit different but not too much in terms of the estimated production function
- What is more is that the allocative efficiency uniformly seems to decline across institutes and estimation procedures

Table 7: Misallocation Analysis: Asinh Patents

IC Name	$\hat{\beta}_{OLS}$	$\hat{\beta}_{FE}$	$\hat{\beta}_{AB1}$	$\hat{\beta}_{AB2}$	$\hat{\rho}_{AB1}$	$\hat{\rho}_{AB2}$	E_{OLS}	E_{FE}	E_{AB1}	E_{AB2}
Aging	0.2018	0.2153	0.2004	0.1511	-0.1201	-0.2171	0.8959	0.8893	0.8966	0.9206
Diabetes	0.1917	0.1848	0.2174	0.1965	-0.1788	-0.2849	0.9104	0.9139	0.8970	0.9079
Drug Abuse	0.0941	0.1018	0.0415	0.0198	-0.0503	-0.0822	0.9618	0.9588	0.9826	0.9916
Env Health	0.1287	0.1717	0.1918	0.1902	-0.1358	-0.1672	0.9333	0.9123	0.9025	0.9033
Eye	0.2654	0.2624	0.3022	0.2861	-0.1149	-0.1640	0.8399	0.8427	0.8004	0.8188
General Medical	0.2978	0.2883	0.2759	0.2783	-0.1854	-0.2889	0.8630	0.8678	0.8739	0.8727
Heart, Lung, and Blood	0.1925	0.1749	0.2607	0.1936	-0.1529	-0.2958	0.9401	0.9458	0.9168	0.9398
Human Genome	0.3092	0.2913	0.4033	0.3917	0.1031	-0.0616	0.4790	0.5102	0.3162	0.3356
Mental Health	0.1108	0.1022	0.1928	0.1972	-0.0748	-0.2751	0.9669	0.9694	0.9435	0.9422
Neurological Disease	0.1989	0.1956	0.1480	0.1199	-0.1528	-0.2726	0.9305	0.9317	0.9484	0.9581
Nursing Research	0.0381	0.0446	0.0580	0.0386	-0.0842	-0.2430	0.9879	0.9859	0.9819	0.9878
Alcohol Abuse	0.0774	0.0775	0.0624	0.0652	-0.0360	-0.1882	0.9681	0.9681	0.9739	0.9728
Allergy	0.1880	0.2006	0.2303	0.1442	-0.0462	-0.0855	0.9131	0.9077	0.8952	0.9320
Arthritis	0.2243	0.2289	0.1962	0.1736	-0.1422	-0.2406	0.9161	0.9144	0.9263	0.9344
Biomedical	0.4747	0.4376	0.4648	0.4794	-0.1742	-0.3257	0.7279	0.7675	0.7393	0.7221
Cancer	0.2127	0.1829	0.3548	0.2461	-0.1239	-0.3112	0.8733	0.8944	0.7232	0.8467
Child Health	0.0891	0.0802	0.1019	0.0949	-0.1421	-0.2293	0.9623	0.9660	0.9570	0.9600
Deafness	0.1595	0.1619	0.1178	0.1137	-0.0589	-0.2054	0.9273	0.9263	0.9449	0.9466
Dental	0.2036	0.1964	0.2146	0.2103	-0.0714	-0.1984	0.9176	0.9204	0.9134	0.9150

Note: This table displays the estimated innovation production function in equation (1) by research area where innovation is defined the number of patents. Then, we compute the estimated loss in aggregate research productivity implied by equation (5) given the estimated research productivities A_{it} and their associated distortions τ_{it}.

- Results suggest much lower returns to scale than the knowledge production function.
- As a result, the misallocation is not too severe because money is much less an important input in the patents production function than the knowledge production function.

Table 8: Misallocation Analysis: Asinh Patents (Cit. Weighted)

IC Name	$\hat{\beta}_{OLS}$	$\hat{\beta}_{FE}$	$\hat{\beta}_{AB1}$	$\hat{\beta}_{AB2}$	$\hat{\rho}_{AB1}$	$\hat{\rho}_{AB2}$	E_{OLS}	E_{FE}	E_{AB1}	E_{AB2}
Aging	0.1349	0.1475	0.0841	0.0682	-0.0533	-0.1374	0.9312	0.9250	0.9562	0.9642
Diabetes	0.1209	0.1130	0.1215	0.1000	-0.1538	-0.2202	0.9518	0.9550	0.9516	0.9600
Drug Abuse	0.0680	0.0793	0.1040	0.0602	0.0198	-0.0902	0.9735	0.9693	0.9603	0.9765
Env Health	0.0871	0.1147	0.1296	0.1208	-0.1459	-0.2247	0.9522	0.9381	0.9307	0.9351
Eye	0.2037	0.2116	0.2187	0.2174	-0.1872	-0.2543	0.8774	0.8709	0.8649	0.8660
General Medical	0.2198	0.2108	0.1755	0.1596	-0.1188	-0.2243	0.8847	0.8901	0.9098	0.9184
Heart, Lung, and Blood	0.1225	0.1070	0.2076	0.1273	-0.1167	-0.2767	0.9610	0.9660	0.9316	0.9594
Human Genome	0.3211	0.3005	0.3704	0.3674	0.0427	-0.1249	0.3961	0.4344	0.3089	0.3140
Mental Health	0.0883	0.0783	0.1509	0.1691	-0.1590	-0.3473	0.9682	0.9718	0.9443	0.9369
Neurological Disease	0.1263	0.1266	0.1735	0.1802	-0.1492	-0.2054	0.9501	0.9500	0.9306	0.9277
Nursing Research	0.0166	0.0251	0.0295	0.0004	-0.0455	-0.2733	0.9952	0.9927	0.9915	0.9999
Alcohol Abuse	0.0483	0.0448	0.0218	0.0318	-0.0755	-0.1704	0.9793	0.9807	0.9905	0.9862
Allergy	0.1369	0.1435	0.2073	0.1438	0.0039	-0.1216	0.9301	0.9269	0.8958	0.9268
Arthritis	0.1444	0.1418	0.1343	0.0866	-0.1653	-0.2851	0.9470	0.9479	0.9505	0.9674
Biomedical	0.3744	0.3379	0.3257	0.3120	-0.1670	-0.2948	0.7772	0.8094	0.8191	0.8295
Cancer	0.1666	0.1421	0.2853	0.1586	-0.2023	-0.3958	0.8750	0.8970	0.7301	0.8823
Child Health	0.0633	0.0513	0.0754	0.0440	-0.0107	-0.1759	0.9636	0.9706	0.9565	0.9749
Deafness	0.1070	0.1008	0.1070	0.1093	-0.0893	-0.2015	0.9525	0.9551	0.9525	0.9516
Dental	0.1286	0.1138	0.0868	0.0854	-0.1004	-0.2122	0.9424	0.9491	0.9611	0.9617

Note: This table displays the estimated innovation production function in equation (1) by research area where innovation is defined the number of citation weighted patents. Then, we compute the estimated loss in aggregate research productivity implied by equation (5) given the estimated research productivities A_{it} and their associated distortions τ_{it}.

- Evidence suggests that returns to scale of production function are quite low, so there allocation matters less.
- Indeed, the allocation of funds is not too far from a hypothetical innovation frontier and – compared to the unweighted patent counts – closer to the ideal.

5 Quantifying misallocation

5.1 Distributions of wedges, patterns and misallocation

1. Patterns of research productivity and distortions
    - report the τs
    - report $Cov(\tau, a)$
    - Another look at misallocation: Scatter plot A_{it} versus G_{it}; or, more precisely: $A_{it}^{\frac{1}{1-\beta}} / \sum_i A_{it}^{\frac{1}{1-\beta}}$ versus G_{it}/G_t
    - How big are the $\mathcal{E}$s and how much do they vary?
    - How much does $\mathcal{E}$ vary with β? How much with $Cov(a_{it}, g_{it})$?

- How do distortions look like over time? Does $\tau_{it} >> 0$ imply $\tau_{it+1} << 0$? I.e. is the government always "taking turns" across recipients? The persistence. Talk to Cem about the time horizon.

add: time series evidence: wild swing over time by institute? Are there aggregate/industry-specific trends?

5.2 Overheads

Other patterns of interest

- How do the A_{it} (or just the FE a_i) correlated with recipient overheads? (From other data source, Cem looks into that.)
- In what areas is efficiency low for papers but high for (break-through) patents? Vice versa?

5.3 Discussion and Counterfactual

- What do the $\mathcal{E} = 1$ mean in terms of number of additional papers/patents?
- What are consequences of funding cuts for papers/patents?
  - Assuming symmetric cuts, i.e. intensive margin, which does translate into lower aggregate G
  - With heterogeneous βs what is effect of symmetric cut across fields, versus cuts in high-β fields?
  - Selected cuts within fields?
  - Show that selection in high-β fields is much more beneficial than in low-β fields.

6 Conclusion and Outlook

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Online Appendix

A Estimation of award-level production function

In this section, we develop an alternative procedure to the one laid out in section 4. Here, we estimate a production function at the level of individual grant j. In the main body of the paper, we assumed that funding recourses within a research agency/university were perfect substitutes and the identity of a grant did not matter for the output as long as one accounted for the productivity of the agency A_{it}. But one may consider the possibility that individual grants do matter and grant money is associated with non-constant returns to scale at the grant level. This means we would have to estimate β at the grant level, which was assumed to be unity in the recipient-level setup of the paper.

Our setup has to be modified in several ways: First, the research productivity is assumed to have recipient-specific permanent and transitory component as before, but there is also a grant-specific component; research productivity therefore is:

$$\begin{aligned} a_{it} &= a_i + b_{it} + c_{ijt} \\ &= a_i + \rho b_{it-1} + \eta_{it} + c_{ijt} \end{aligned}$$

Note that c_{ijt} is the idiosyncratic component of a project financed by award j, which happens to be given to recipient i in year t. There is no persistence in c_{ijt} because award j is only given once.

One challenge arises in the Arellano-Bond procedure for this setup as there is no panel of grants in the sense that an award given in one year realizes again in other years. We circumvent this problem by averaging all grants of a recipient i in a given year t. This "average grant-level knowledge production function" can be interpreted as a the production function of a representative grant, and it then becomes:

$$y_{i\bullet t} = a_i + b_{it} + c_{i\bullet t} + \beta g_{i\bullet t}$$

where $\bullet$ indicates an average across all j given to i in t. Now it does not matter if an institution i receives a lot of grants in one period and few in another as long as there is at least one grant to consider. This naturally assumes that award characteristics are orthogonal to the number of awards given to a specific recipient. Rewriting this

$$\begin{aligned} y_{i\bullet t} &= a_i + b_{it} + c_{i\bullet t} + \beta g_{i\bullet t} \\ &= a_i + \rho b_{it-1} + \eta_{it} + c_{i\bullet t} + \beta g_{i\bullet t} \\ &= a_i + \rho \left[y_{i\bullet t-1} - a_i - c_{i\bullet t-1} - \beta g_{i\bullet t-1} \right] + \eta_{it} + c_{i\bullet t} + \beta g_{i\bullet t} \\ &= (1-\rho) a_i + \rho y_{i\bullet t-1} + \beta g_{i\bullet t} - \rho \beta g_{i\bullet t-1} + c_{i\bullet t} - \rho c_{i\bullet t-1} + \eta_{it} \end{aligned}$$

To estimate β (and ρ), we instrument for the RHS variables using $\{\Delta y_{i\bullet t-2}, \Delta g_{i\bullet t-2}, \Delta g_{i\bullet t-3}\}$ all of which are orthogonal to η_{it}, $c_{i\bullet t}$ and $c_{i\bullet t-1}$.

Alternatively, we can estimate equation (7) in first differences:

$$\Delta y_{i\bullet t} = \rho \Delta y_{i\bullet t-1} + \beta \Delta g_{i\bullet t} - \rho \beta \Delta g_{i\bullet t-1} + \Delta \eta_{it} + \Delta c_{i\bullet t} - \rho \Delta c_{i\bullet t-1}.$$

To maintain orthogonality with $\Delta \eta_{it}, \Delta c_{i\bullet t}, \Delta c_{i\bullet t-1}$, we choose $\{y_{i\bullet t-3}, g_{i\bullet t-3}, g_{i\bullet t-4}\}$ as instruments.

Compared to the recipient-level production function, the grant-specific productivity term causes orthogonality problems, which requires lagging instruments one more period than in the main setup. With instruments that have to be lagged that many periods, instrument relevance will of course become an issue as will sample size.