Title: Is Bigger Better? Lab Productivity and Lab Size

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Although laboratories are ubiquitous features of Science, which and what types of scientific labs should receive government funding remains a topic of ongoing and often contentious debate[1]. Recently, there have been prominent assertions that labs have grown too large to be productive[2, 3, 4], prompting calls for the halcyon days of small groups, such as those at the Medical Research Council Laboratory of Molecular Biology[5]. To address these concerns, the Howard Hughes Medical Institute has invested billions of dollars to construct Janelia Farm[5], and the US National Institutes of Health (NIH) scrutinizes a lab's total funding levels when assessing new funding decisions[6]. However well meaning, these policies have been put in place based upon intuition and experience, rather than rigorous analysis[7]. Here I show that productivity measures commonly used in management can be readily adapted to the assessment of lab productivity, with starkly new prescriptions. Specifically, I stress that labs should be rewarded for the conversion of inputs to outputs, rather than a singular focus on increasing outputs (i.e., papers). I apply this productivity metric to data from the MIT Department of Biology and find a *positive* correlation between publication output (i.e., traditional productivity measure) and larger labs, but a *negative* correlation between this paper's productivity measure and larger labs. Lastly, I show that the use of my productivity metric would have shifted over 20% of the funds allocated to MIT biology. Thus, if adopted by granting agencies such as the NIH, this metric could easily reshape the funding landscape on the order of billions of dollars per annum.

How should we measure a laboratory's productivity? This assessment, that past productivity predicts future promise, undergirds activities ranging from grant funding, tenure, job placements, and the recruitment of future talent. In short, it is no overstatement to say that the assessment of lab productivity permeates every facet of the scientific enterprise[3]. The most common method used to assess laboratory productivity is a journal (impact factor) weighted count of publications (hereafter, JIFcount), or some close variant[8]. And yet, this measure stands in stark contrast to well-established productivity measures in management. Specifically, business managers emphasize accounting ratios[9]. Ratios stress rewards for the effective *conversion* of inputs (assets) to outputs (profits), rather than a singular focus on increasing outputs (e.g., papers). Without taking into account per asset productivity ratios, businesses would exhibit undisciplined growth.

In this paper, I adapt the most widely used financial accounting measure, the ratio of net income to assets (ROA). Developed a hundred years ago at the DuPont Corporation, ROA describes the efficiency through which a firm converts assets to desired outputs[9]. Moreover, it separates the firm's activities into two disparate ratios. Profit margin captures the pricing strategy, and asset turnover captures volume. Multiplied together, profit margin and asset turnover yield ROA (Figure 1).

How might ROA be adapted to measure lab productivity? For the outputs, the obvious choice is a journal-weighted publication count, such as JIFcount. Although actual citation counts are another measure widely used in scientometrics, these measures are considerably more complex and involve vintage and field normalizations[10]. The inputs, a correlate of lab assets, yield more options, but the most pragmatic choice is a simple count of lab members (i.e., lab size). Personnel costs, including such related expenses as salary, workspace, tuition and benefits, and disposables, is by far the largest line item in a laboratory's operating expenses. Borrowing from Bruce Alberts' 1985 commentary in Cell, I call this ratio of JIFcount to Labsize: Per Capita Productivity (PCP)[1] (Figure 1).

The PCP measure can be further deconvoluted into its constituent ratios. Papers published in secondary journals often take as much effort as prominent ones. Thus, Impact Margin (IM) describes the return on publication effort, or the proportion of published papers that occur in high-profile journals. In contrast, Per Capita Output (PCO) describes the volume of publications generated per lab member. While a high volume of prominent papers is ideal, the constituent ratios stress that a high PCP can also be achieved through either prominent publications (IM) or through volume (PCO).

To illustrate the operationalization of the ratio measures, I examine the inputs and outputs of laboratories at MIT Biology, from 1966 to 2000[11]. This dataset has many advantages. Having received a doctorate from this department, I had unparalleled insight into the setting. Moreover, during this timeframe, the department published an Annual Report, providing a complete personnel roster for each laboratory. Lastly, I collect detailed data from Medline, yielding both publication counts as well as JIFcount, to document research output.

My analysis tracks 91 labs over 1,090 laboratory-years (the unit of observation). The average laboratory published 3.9 papers with the Principal Investigator (PI) as a last-author each year, yielding a total JIFcount of 34.4. The typical laboratory had 7.9 lab members, not counting the PI.

Computing ratios, each lab member generated 0.56 publications per year (PCO) and each paper generated an average of 8.5 citations (IM). Overall, the average per capita productivity was 4.6. Phrased in this manner, each lab member generated 4.6 expected citations in a given year.

To illustrate the salience of these productivity measures, I apply the PCP measure to two pressing policy issues. First, I reexamine the relationships between lab size and productivity. Second, I examine how adoption of the PCP measure would reallocate NIH funding to MIT Biology.

Lab Size: Recently, there has been a vibrant debate on lab size and productivity[2,5,6,12]. To rigorously examine this relationship, Figure 2 reports results from Poisson regressions of next year's productivity ratios on this year's lab size using MIT Biology data. As these regressions contain laboratory fixed effects, they correlate changes in laboratory size with changes in productivity while controlling for both observed and unobserved time-invariant attributes of the laboratory (e.g., discipline, model organism, PI, et cetera). For simplicity, I report the predicted consequences (with confidence intervals) of adding an additional lab member on alternative measures of lab productivity.

In Figure 2 Row 1, I first report the effects of lab size on a prototypical outcome measure: JIFcount. It comes as no surprise that larger laboratories have higher output: adding an extra lab member increases JIFcount by 4.4% ($P < .001$).

In direct contrast, the use of my PCP measure in Row 2 suggests that although larger labs produce more JIFcounts, they are less efficient at converting lab members to output. Adding an extra lab member decreased overall productivity by 3.4% ($P < .001$). Rows 3 and 4 shed light on the mechanism. Adding a lab member increases the average impact factor of each publication by 1.9% ($P < .001$), but also results in 5.2% fewer publications per lab member ($P < .001$). As the decrease in PCO dominates, overall lab productivity decreases as lab size increases. Phrased differently, larger labs are publishing relatively fewer papers, but shifting these papers towards more prominent journals.

NIH Funding: How might the use and adoption of the PCP measure affect grant funding at the U.S. National Institutes of Health (NIH)? The pairwise correlation between JIFcount and PCP is high at 0.71. However, the correlation between JIFcount and NIH funding is 0.25, more than 2.7-fold higher than the 0.09 correlation between PCP and NIH funding. To illustrate the importance of this divergence, I rank-ordered lab-years by either JIFcount or PCP, and then tabulated the proportion of NIH funds to each percentile (Figure 3). The positive slope in the trendline shows that a higher percentage of funds went to lab-years with higher JIFcount scores. By contrast, this slope is shallower when using the PCP ranking, suggesting that high PCP labs are receiving less funds than expected, while low PCP labs are receiving more.

In short, the use of the PCP measure would result in a significantly different allocation of NIH funds. Using actual dollars received, I calculate that the top 25% of JIFcount-ranked lab-years received 10.3% more of total NIH grant dollars than the top 25% of PCP-ranked observations. Moreover, the bottom 50% of PCP-ranked observations received 12.5% more funds than the bottom 50% of JIFcount-ranked observations. Overall, these differences aggregate to ~$174 million (year 2000) dollars at MIT Biology alone. Given NIH's yearly extramural allocation of ~$30 billion per year, it is highly plausible that the adoption of the PCP measure would shift many billions of dollars in funding per annum.

Discussion: So is bigger better? This analysis would say not, consistent with widely publicized policies such as NIGMS' decision to cap the support of their extramural investigators[2,4,6]. However, my analysis also suggests that a blanket ceiling on a PI's funding levels is unwise. Instead, we need more precise measures of productivity, allocating money to labs that can best utilize the funds.

First, although the typical lab may be less productive as it grows, some large labs remain highly effective. By focusing on *per capita* productivity, the PCP measure endogenously corrects for the issue of laboratory size and, implicitly, funding levels. Moreover, the PCP measure may help to identify particularly effective labs, and analysis of their managerial practices may provide further mechanisms to increase lab productivity[13].

Second, larger labs have a higher Impact Margin, but a lower Per Capita Output. It remains possible that breakthroughs from large labs would not occur if they were smaller, although correlates of size, such as status effects are an alternative explanation[14,15]. If breakthroughs disproportionately accrue to larger labs, decreasing diseconomies of scale (i.e., low PCO) may be wiser than capping lab size. For example, the incorporation of experienced research scientists or other changes in the organizational structure may be particularly beneficial[4,11].

A major advantage of the PCP measure is its simplicity. For example, to incorporate PCP into the funding potential of a lab, assessors only need the number of current lab members. That is all. Thus, the implementation of the PCP measure is not onerous on the part of PI. Moreover, PCP sidesteps reporting of the funding source. Rather it captures the conversion of taxpayer dollars to scientific output[6].

Relative to the majesty of scientific discovery, accounting is dull. However, accounting practices are already here, and here to stay. Instead, the PCP measure provides a *better* accounting measure, taking into account not just a PI's CV, but also the laboratory social structure that surrounds the PI[16-18]. Ultimately, I remind the reader that there is no accounting replacement for human creativity. Without that, science would be a dry landscape indeed.

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Figure 1: Adaptation of Return on Assets Ratios to Laboratory Productivity

A)
$$\underset{\textbf{(ROA)}}{\textbf{Return on Assets}} = \underset{\textbf{(PM)}}{\textbf{Profit Margin}} \ \mathbf{X} \ \underset{\textbf{(AT)}}{\textbf{Asset Turnover}}$$

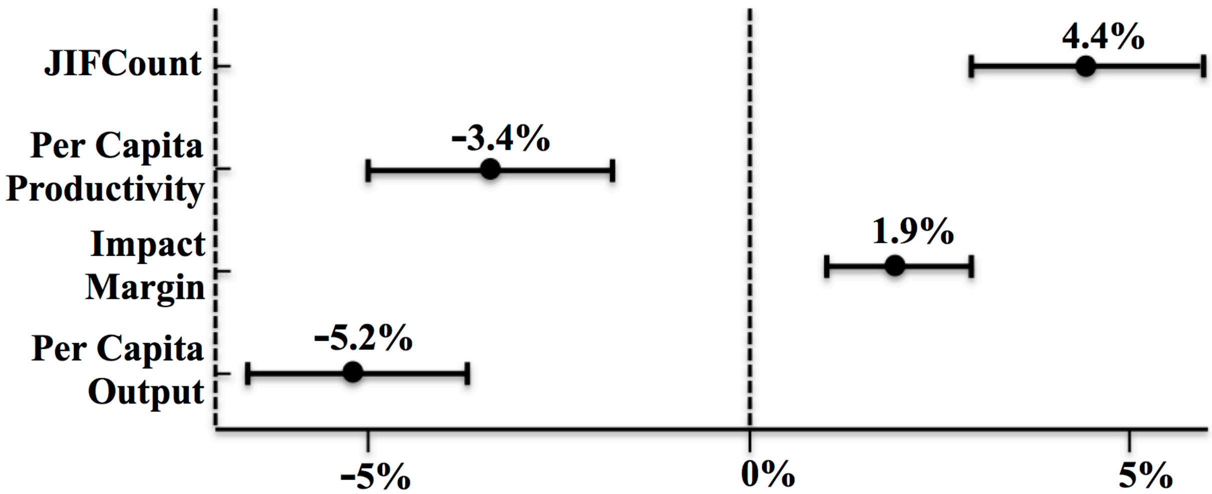
$$\frac{\text{Net Income}}{\text{Assets}} = \frac{\text{Net Income}}{\text{Sales}} \ \mathbf{X} \ \frac{\text{Sales}}{\text{Assets}}$$

B)
$$\underset{\textbf{(PCP)}}{\textbf{Per Capita Productivity}} = \underset{\textbf{(IM)}}{\textbf{Impact Margin}} \ \mathbf{X} \ \underset{\textbf{(PCO)}}{\textbf{Per Capita Output}}$$

$$\frac{\text{JIFcount}}{\text{LabSize}} = \frac{\text{JIFcount}}{\text{Pubcount}} \ \mathbf{X} \ \frac{\text{Pubcount}}{\text{LabSize}}$$

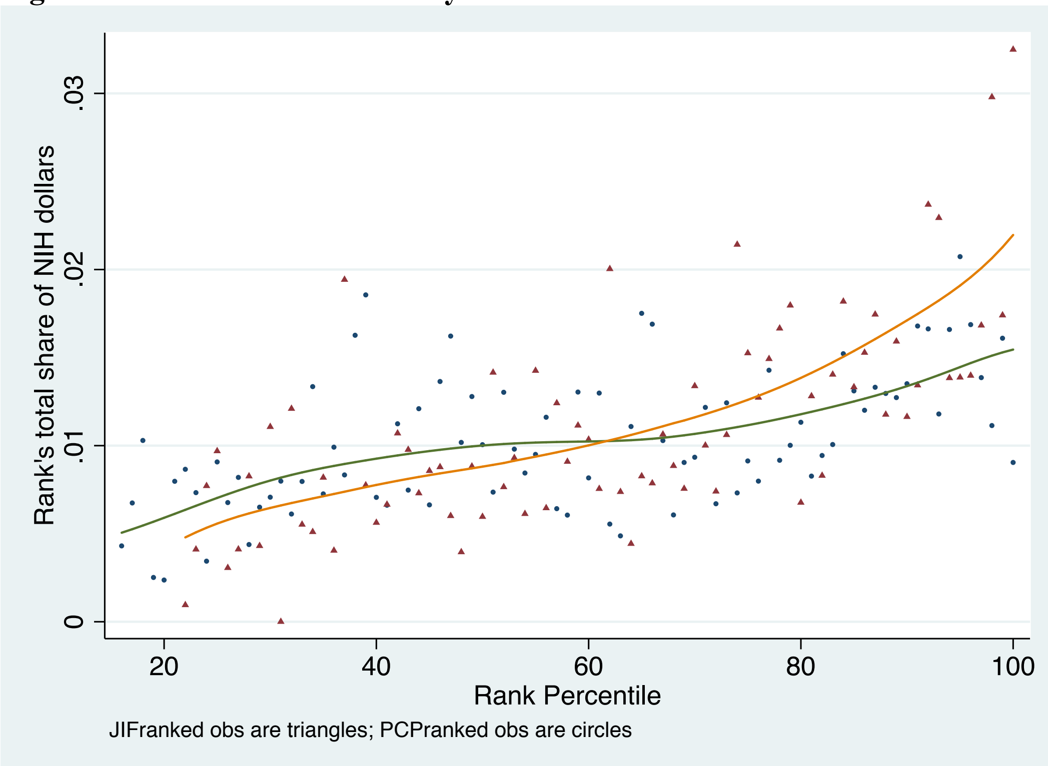
Note: Pubcount is the yearly number of publications that the laboratory produces. JIFcount is the total journal-impact-factor (JIF) that these publications are expected to produce.

Figure 2: Lab Size and Lab Productivity



Note: The predicted consequences of adding an additional laboratory member on four different productivity measures are reported in each row. The figure shows effect sizes and 95% confidence intervals from Poisson regressions. These effects are statistically significant if 0 falls outside of the confidence interval. Bars to the right of the stippled line indicate a positive correlation between lab size and the productivity measure. Bars to the left indicate a negative correlation. Full regression tables are presented in Table S-2.

Figure 3: NIH Funds allocated by JIFcount-Rank and PCP-Rank.



Note: The unit of observation is a Rank Percentile. Laboratory-year observations were rank-ordered by either a) JIFcount or b) Per Capita Productivity and aggregated into Rank Percentiles. Each Rank Percentile's share of total NIH dollars (over all years) is graphed on the Y-axis. If productivity measures were not a correlate of NIH funding, the smoothed (Lowess) curves would be flat. The smoothed curve for JIFranked observations is show in (light) orange, the curve for PCP ranked observations is shown in (dark) green. All NIH dollars were adjusted to reflect year 2000 values.