Incentivizing Pro-social Behavior in Governance: The Effects of Revealing Peer Rankings on Voluntary Service[1]

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Abstract

We implement a field experiment at a U.S. university to identify the effect of revealing peers' rank, in terms of previous voluntary service, on future voluntary service of individual faculty members. We find that revealing a service ranking in the lowest quartile leads to significantly higher response rates than disclosing a median quartile ranking. Beyond informing the department head, sending a direct email to individuals does not have an incremental effect on average voluntary service responses, though it causes significantly higher new response. Finally, we find the above effects are driven by male responses.

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I. Introduction

Governance–the way rules are set and implemented–in many institutions is maintained through the voluntary service of groups of individuals, where its success depends on the willingness of individuals to serve. With the objective to examine methods that could encourage participation in governance, we implement and analyze a field experiment to identify the effect of revealing peers' rank, in terms of previous voluntary service, on future voluntary service.

The principle of shared governance, while contributing to the excellence of many public U.S. universities, depends on the willingness of the faculty to exercise it, by voluntarily serving on the academic senate and on campus committees over the course of their academic tenure at such universities. When serving on committees, individual faculty dedicate time to participate in the way rules are implemented and decided, and consequently benefit by having a voice in discussions vital to the governance of the institution. On a more aggregated level, departments may want to have a large share of their faculty serving on committees because it is by such service that a particular department can have its interests represented, in all manner of decisions affecting faculty lives as teachers, researchers, and employees. While there are reasons for individual faculty to not want to volunteer due to the time opportunity cost of serving, this is balanced against the fact that participation in service can be an important consideration in advancement and promotion cases for faculty members, especially at the higher levels. Yet despite all these reasons to serve, service calls have low response rates of about 10-20%.[2] If the objective of universities and departments therein is to increase service participation among its faculty members, understanding what motivates faculty to volunteer to serve or not serve is an important first step.

This paper investigates whether providing information to individuals about their ranking relative to their peers in terms of previous voluntary service changes individuals' incentives to voluntarily answer future calls for service. Moreover we investigate whether informing department chairs of relative ranking information (in a top down fashion) instead of informing faculty directly (in a bottom up fashion), leads to similar responses rates. Existing research has empirically established a link between disclosing rankings (or percentiles) and individual

[2] The historical response rate to academic service calls at the public U.S institution in this study varies by departments but remains very low over the years surveyed.

behavior in many settings (e.g., STA scores, restaurant ratings, wine ratings, savings, and pollution emissions). Our paper adds to an extensive literature on the power of social norms to influence pro-social behavior in a variety of settings (see Cialdini and Goldstein 2004, for a review).

Changing behavior in response to the behavior of others is consistent with two distinct hypotheses (Ayres et al., 2013). First, learning that peer departments provide less (more) service could increase (decrease) feelings of guilt and lead to more service in the future. Alternatively, learning the behavior of peers might provide information about the possibility of alternative time use choices of the faculty body and the relative benefits of those choices. Like other peer information studies, this paper will not distinguish between preference and information theories of behavioral change. Specifically, if faculty members react to information that their department is serving more than their peers' by decreasing their own service, this change might be caused either by decreased guilt, or by making a Bayesian inference about missing out and being free ridden by others—since they could be spending their faculty time in research. The gender composition of departments may also be behind the behavioral changes induced from releasing peer information to nudge service participation. For instance, recent research identified gender differences in the probability of taking on service tasks (Vesterlund et. al, 2015), finding that women are more likely to respond to voluntary service calls than men.

We obtained, from public records, data on historical service responses by department as well as the current distribution and number of faculty by academic rank for each department in a large, public university in the U.S. We consider the pool of potential faculty to serve, among each department, as consisting of all faculty that are associate professors or higher, since typically assistant professors are not encouraged to participate heavily in campus service due to the tenure track. Given that number we are able to compute the participation rate by department as the ratio of the number of faculty serving to the number of faculty in the potential service pool.

The empirical design is as follows. For the 64 departments and schools in our sample, we divide departments into small, medium and large sizes, defining size quartiles. Given each size quartile we compute the rates of service by department, and its ranking in terms of percentile in participation rate within its peer size group of departments. We then randomly assign half of departments in each size quartile into a treated group and into a control group. The control group receives a standard call for service reminder email, sent to the department chair or dean of each school. The treated group receives a similar email reminder but, in addition, the departments in this group receive information on what percentile they are, among all departments in their size quartile, in terms of service participation. We then collect data on two years of response data, for the responses pre- and post-intervention to estimate the effect of the information treatment on service response rates by department. For fear of discouraging high service departments from continuing to serve, by disclosing their high service percentile, the highest quartile service rate departments in each size quartile are not treated. This leaves us with 24 treated departments, 24 control department, comparable in size and service, and 16 very high service departments that receive the control email but are not used to identify the treatment effects. As a small orthogonal sub-treatment to the overall experimental design, for a subset of treated departments and comparable controls, all faculty in that subset receive the same email directly, and at the same time as their chair. In this case we wish to assess whether, by informing faculty directly of their department's relative ranking, this bottom up information approach leads to different response rates as to when the chair receives the information and conveys it to their faculty (top down) approach. Our experimental design further allows us to test whether the response is due to new service (i.e., faculty who had not served the year before), as well as whether there are gender differences in the treatment effects.

Our findings are as follows. The probability of replying to the service call increases, on average, when the chair got the treatment email relative to when the chair got a standard control email, and significantly so for faculty new to service. The probability of replying did not change significantly when faculty got directly treated. When we go beyond the average effect and investigate heterogeneity of responses by service quartile disclosed in the chair email, our results show that the lower the service quartile displayed the larger the treatment effect. In other words, the individuals that responded the most originated from departments whose chair received an email disclosing the lowest service quartile, and the lowest response rates originate from departments that got emails disclosing higher service quartiles.

While a direct email to the faculty did not, have a differential incremental effect relative to chair email received, both the direct email treatment and the chair email treatment did cause significantly higher new service responses when the quartiles featured were lower. In other words, if the department was among the top serving, that led to less new service responses for both treatments. Finally, and in terms of gender differences, men respond significantly to the chair email treatment, while women do not.

Our paper is related to the literature on the power of revealing peers information on pro-social behavior. A recent paper, and very similar in approach to ours, by Ayres et al. (2013) finds that, by providing feedback to customers on home electricity and natural gas usage *with a focus on peer comparisons*, utilities can reduce energy consumption at a low cost. In another example, Goldstein et al. (2008) find that peer comparison information could increase towel reuse by hotel guests. Reporting the emissions and rankings of firms in the U.S. Toxic Release Inventory (TRI) and similar "Right to Know" programs in other countries have shown that releasing information on where you stand in terms of the distribution of your peers matters for future decisions of how much to emit and to abate (Schlenker and Scorse, 2014; Hamilton, 1995; Konar and Cohen, 2001; Antweiller and Harrison, 2003; and Blackman et al, 2004) while "Right to Know" programs based on health inspections have influenced the behavior of both consumers and restaurants (Jin and Leslie, 2003).

Our paper is also related to the literature on charitable giving, peer effects, and norms. Smith, Windmeijer, and Wright (2014) find that donors use information on the distribution of earlier donations to decide what is important for them to give. A £10 increase in the mean of past donations increased giving by £2.50, on average. Card, Mas, Moretti, and Saez (2010) find that revealing the salary of peers causes university workers with salaries below the median for their pay unit and occupation to report lower job satisfaction while those earning above the median report no higher satisfaction.

Lastly, related to gender responses to service calls, our paper complements Vesterlund et al. (2015) who experimentally test whether women in another large, public U.S. university are less able to say "no" than men to appeals to non-promotional tasks, such as service, a feature that could explain the gender gap in income of women relative to men. Our set up allows us to investigate directly whether women respond differently than men to the treatments and moreover, whether women respond differently than men, when being directly asked to serve by their chair in a top down fashion.

The paper proceeds as follows. Section II describes the data and experimental design. Section III lays out the empirical strategy. In section IV we present the results. Finally, section V concludes and discusses avenues for future research.

II. The Data and Experimental Design

A. Data Sources and Summary Statistics

The first dataset used consists of administrative survey records on the number of faculty and their academic rank (i.e., assistant, associate professor, and professor) for each department and school in a large public U.S. university. The raw data of the faculty census for the year of 2013 consist of 1719 observations with a faculty identifier, the department affiliation, the academic title (assistant, associate, etc.), and a job-code. Several job-codes in a particular school were not actual faculty senate positions, so these 109 observations were dropped. In the remaining raw data quite a few faculty had multiple affiliations, that is, they were listed as belonging to multiple departments (mostly to two). In those cases, to compute the total number of faculty to each department, if a faculty member is listed as having two affiliations, that member counts as ½ into the count of each of the two departments. This happened for 455 cases. A few faculty had three or more affiliations, that is, $n>2$, and when counting faculty numbers for the departments they are affiliated with, each of those faculty received $1/n$ of weight. As a result, and given the above criteria, we have a final roster sample of 1601 faculty belonging to 64 departments.[3]

Given these data we compute for each department the total number of faculty in the most recent census year of 2013 and we also compute the total number of eligible service pool faculty by department, consisting of faculty of associate title or higher (that is, we exclude all assistant professors). Table 1 presents summary statistics of the total number of faculty members, as well as on the numbers of the eligible faculty member pool by department.

[3] Given that five of the 69 departments mostly teach undergraduate in interdisciplinary units and do not have a core faculty body or chair, they are not used in the analysis, leading to only 64 departments being considered in the final sample.

Table 1. Number of Faculty by Department by Size Quartile in Campus Distribution

	Q1	Q2	Q3	Q4
Number of Faculty by Department	up to 8	up to 16	up to 28	up to 80.5
Number of Faculty (Associate Professor or higher) in the Service Eligible Pool	up to 7.5	(7.5,12]	(12,24.5]	(24.5,72.5]

Q1 is the lowest 25th percentile in terms of eligible pool faculty distribution across departments

Q1 is the highest quartile, 75th percentile or higher in terms of eligible pool faculty distribution across departments

Source: Faculty 2013 census roster by department

The departments in this institution are quite heterogeneous in their size. First, the smallest quartile (labeled Q1, henceforth) in terms of eligible pool size consists of 18 departments with 7.5 faculty or less. The second quartile (Q2) in terms of size has 19 departments with 7.5 to 12 faculty members that are eligible for service. The next quartile, Q3, has fifteen departments with the number of eligible faculty ranging from 12 to 24.5. Finally, the largest size quartile Q4 has the remaining 17 departments and those are departments that are quite large, with up to 72.5 faculty members in the eligible service pool.

The second dataset we use originates from the administrative records and consists of the aggregate number of faculty serving in the senate for each department for the years of 2005 to 2013.[4] Given historical data on the service responses by department and the number of faculty in each department, we compute the percentage of eligible faculty (associate and higher) in the last year to classify the departments according to 2013 service quartiles. It is according to these quartile numbers in 2013 that we define the high, medium and low department. Then we randomly assign departments into treatment and control groups for similar department size and quartiles. We check using the time-series historical data whether departments in the treatment and control groups have similar service trends.

Table 2 provides a breakdown of service participation summary statistics by department in 2013. The table is organized by size quartiles Q1 to Q4 in columns and service rates summary

[4] Every year faculty answer by email or verbally a call to serve and these are the numbers of those that end up serving. In terms of percentages, this is mostly the bulk of people willing to serve on campus. In 2013, only 8 faculty members, among 312 who volunteered to serve, were not assigned to campus committees - and this was due to all 8 originating from a faculty field that was already heavily represented on the committees.

statistics in rows. In the first row we have the average participation rate, then in the second row the median participation rate, in the third row the maximum participation rate, and in the bottom row the number of departments.

Table 2. Average Departmental Service Partipation Summary Statistics by Size Quartiles

	Q1	Q2	Q3	Q4
Average service participation	18.80%	32.50%	27.10%	22.80%
Median Participation	0%	31.50%	24.30%	24.20%
Maximum Participation	75%	75%	58%	34%
Number of Departments	18	19	15	17

SQ1- lowest 25th percentile in service rates among peers of same size, and SQ4 is the 75th or higher percentile in service for departments of same size. Q1 is the lowest 25th percentile in terms of eligible pool faculty distribution across departments

Q1 is the highest quartile, 75th percentile or higher in terms of eligible pool faculty distribution across departments

Source: Faculty 2013 census roster by department

The departments that have the highest average participation rate on campus are the small-medium size departments in Q2, with 32.5%. They also have the largest median participation rate across all sizes. For the smallest size quartile, Q1, more than half of the departments have no service participation, as the median is 0%. This could be consistent with the fact that those very small departments are already fully involved in internal departmental level service and their faculty members do not have time to participate in campus level service in addition to the departmental level one.

In the third row, we see that the smaller departments in Q1 and have the largest maximum department service participation of 75%. This is not surprising by the mechanical fact that there are fewer faculty numbers in those departments. That number can be as low as 2.5 in Q1 in some cases, and therefore if one of those few faculty is involved in service, then the resulting service participation rate is quite high as a mechanical result of the faculty number in the denominator being so small. This is why it is important to analyze service rate participation and compare departments within their peers in terms of similar size. And we do this by comparing departments in each column, not across columns. For the largest size quartiles, the maximum participation rate is 58% in Q3 and 34% in Q4.

To recap, we have a panel dataset of service records over time aggregated at the department level; we have a cross sectional census of faculty affiliation by department; we know whether every faculty member has served in committees in the past or not; and we have two years of replies data, to the call to service, at the individual faculty level for the last two years only.

B. Experimental Design

Within each department size quartiles (Q1-Q4), we divide departments into four service quartiles (SQ1 ≤ 25th percentile in terms of service, SQ2 = 26-50th service percentile; SQ3 = 51-75th service percentile, and SQ4 ≥ 75th service percentile). Next, within each department size and service quartile group, except the highest service quartile, we randomly assign departments into a treatment and into a control group. We do not treat the high service departments (defined as SQ4) for fear of discouraging service. We therefore only make an experimental intervention on the three lowest service quartile departments, SQ1 to SQ3, and leave the upper quartile SQ4 departments unchanged.[5] Furthermore, the randomization is not stratified on previous service participation.

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[5] In the original research design those departments also were assigned into treatment and controls, to test whether disclosing high percentiles would encourage or discourage future service responses. However we did not find institutional support to implement this additional test from the data source. We opted to follow their recommendation, given their willingness to share these unique data made this study possible in the first place.

Table 3.Number of Departments in the Treatment and Control Groups, and the untreated departments

	SQ1- control	SQ1 - treated	SQ2- control	SQ2 - treated
Size Q1	1	4	none	none
Size Q2	1	3	3	3
Size Q3	2	2	1	2
Size Q4	3	2	2	2
	SQ3- control	SQ3 - treated	SQ4- not treated	
Size Q1	4	none	4	
Size Q2	2	2	5	
Size Q3	3	2	3	
Size Q4	2	2	4	

SQ1- lowest 25th percentile in service rates among peers of same size, and SQ4 is the 75th or higher percentile in service of same size. Q1 is the lowest 25th percentile in terms of eligible pool faculty distribution across departments

Q1 is the highest quartile, 75th percentile or higher in terms of eligible pool faculty distribution across departments

Source: Faculty 2013 census roster by department

The number of departments in each service quartile cross-tabulated with each size quartile, for the treatment and control group, is presented in Table 3. One important feature of this design is to investigate first whether the control and treatment groups are comparable in attributes, such as the number of faculty, the number of departments, and average service in the pre period. Another important thing to investigate is whether the departments in the treatment and control groups have similar pre-treatment trends in terms of service responses. This is investigated next.

Table 4 presents the summary statistics of observable characteristics for treatment and for control departments, where we do not include observations for the highest service quartile departments in SQ4. In the end we have 24 treated departments with 627 faculty and 24 comparable control departments: which have a total of 577 faculty, associate professor or higher. In terms of the untreated departments in the top service quartile SQ4, there are a total of 16, with a total of 272 faculty members.

Table 4. Observable Average Comparison Treatment and Control Groups

	Control - chair Email only	Treated - chair Email only	Control - Chair+ Faculty Email	Treated - Chair+ Faculty Email
Number of Departments	18	18	6	6
Number of Faculty	503	491	124	86
Number Women	151	118	39	25
Average Faculty by department	23	21	15	10
Average Females by Department	8	6	7	4
Average Service in pre period	23%	18%	23%	12%
Trend in Service since 2005	-0.012	-0.003	-0.002	-0.015
Females Serving/Total Females	15%	13%	28%	9%

Source: Authors' calculations.

In the first two columns of Table 4 we report summary statistics for the control and treatment groups to the chair and then in columns 3 and 4 for the sub-treatment, consisting of an email directly to faculty members in the control and treated groups, respectively, where we send the email reminder directly to faculty for 6 departments among the 24 originally treated with the chair email, with the same treatment message. We also send the control email directly to faculty in 6 out of the 24 original control departments that received the control email to the chair.

There are a total of 18 departments who receive the standard control reminder email to the chairs and then 18 departments receive the treatment email to the chairs. These two groups have comparable pre-treatment average departmental service, of 23% and 18% respectively, the average number of faculty per department are very similar, namely, 23 and 21. Finally in terms of observables, the total number of faculty eligible to serve in both departments is very comparable, 410 and 399. In terms of pre-existing trends in service participation since 2005, service in both departments groups had been declining significantly, by -0.012 and -0.003, respectively. Doing an F test for equality of pre-period trends, we cannot reject that both trends are the same, with an F-stat=0.92 and a p-value of 0.3378. For the last two columns in Table 4, we compare the sub-treatment and sub-control groups, in terms of observables and pre-existing trends. Recall that these sub treatments not only receive the same emails to chairs as in the corresponding treatment and control groups, in addition, these departments' faculty members receive an individual targeted control or treatment email calling for service. Once again we find those to be quite similar, although, all the observable averages in terms of service, average faculty per department, and total number of faculty are slightly lower in the last column (Treated Chair + Faculty Email) than in the Control Treatment and Faculty email column. More importantly though, the pre-existing trends are once again both negative and we cannot reject the null hypothesis that they are equal (with an F-stat=1.35 and p-value of 0.224).

In terms of female faculty, the number of female faculty is always lower than the number of men for both the treatment and control groups, and very comparably so across all columns. Interestingly, as we can see in the last row of Table 4, the percent of women serving among women in each department is around 9 to 13% in the treated groups and somewhat higher between 15-28% in the control groups. As a conclusion, the data show that neither men nor women have reached full service capacity in the pool of potential respondents, and this is true in all departments, for both the treatment and the control groups.

III. Empirical Strategy and Testable Hypotheses

The control group chairs receive a standard reminder email from the Chair of the Committee that recruits service on campus. This email is similar to a reminder they receive every year. The treated email chairs receive the same email but with additional information on where their department ranks in terms of service. In particular, the treated email reveals to the chair the quartile of the department in terms of service participation among departments of similar size (i.e., in the same size quartile). Given that we do not treat the highest service quartile departments, the tone of the treatment email encourages the departments to improve the participation rate in the future.

The standard email, sent to the control chairs, starts with "Dear Chair. We would like to thank you and your faculty for your continued service! We remind you and your faculty members to complete the call for service for the year 2014-15 by following the link below. Please forward this email to your faculty and have them reply by date […]." In the treatment email we say "Dear Chair, Thank you for the service your department has given to campus! Given data on 64 departments and compared to your peer departments of similar size you are among the X *quartile (y^{xth} percentile) (*) in terms of service participation in 2013 and 2014*. We would like to encourage you and your faculty to respond to the service call and have your department have a stronger voice on campus governance. Please complete the call for service for the year 2014-15 by following the link below and sending this email to your faculty." X varies according to the service quartile of each department**,** that is, *(*) X would vary between, "lowest first quartile (y=25th percentile)", "second lowest (y is between 25th and 50th percentile)/ or below median" and "around median" (y is for those in 50-75th percentile) .*

Our email experiment has three testable hypotheses. First, departments may not know their service participation rate quartile X and also do not know how much service participation rates other comparable departments have, given that this information is hard to gather from available administrative records. Thus, if we inform them of their ranking (giving them the quartile of where they are in the size-peer distribution), we can test whether this new information affects the response rate of the call to serve. Second, if we inform them that they are not doing as well as others among their peers (or doing better than their peers), we can test whether this negative (or positive) comparison leads to an effort to improve and increase replies. Third, if we email the rankings not only the department chair but also to the individual faculty members directly, we test can whether top-down versus bottom-up strategies have differential effects on the response rate to the call to serve.

Given the responses to the intervention service call by a faculty member f from department d, we compare the response indicator, R_{fd} *=0 or 1,* among faculty from treated and control departments, controlling for observed characteristics, in the following specification

$$R_{fd} = \alpha + \beta_s Size_d + \beta_q Quartile_d + \gamma_1 Treat_d + \gamma_2 DirectEmail_d + \gamma_3\, DirectEmail_d * Treat_d + \varepsilon_{fd} \qquad (1)$$

where α is a coefficient that captures the average response, $Size_d$ is a variable corresponding to the size quartile of department *d*, $Quartile_d$ is a variable corresponding to the 2013 service quartile of department *d* among its peers of similar size (i.e., $Quartile_d = 4$ if the department is in the highest quartile, $Quartile_d = 3$ if the department is in the third quartile, and so on), and β_s and β_q are the coefficients beta to be estimated. In terms of the coefficients of interest with respect to the experiment, those are associated with the variables $Treat_d$ and $DirectEmail_d * Treat_d$. In particular, the estimate γ_1 corresponds to the average treatment effect of sending a treatment email only to chairs. The estimate γ_2 corresponds to the incremental average responses due to sending an email directly to faculty, measured by the variable $DirectEmail_d$. Finally, the estimate γ_3 corresponds to the causal incremental change in responses due to sending a treatment email directly to faculty, relative to the chair's average treatment effect estimated by γ_1 and relative to the average effect of a direct email estimated by γ_2.

In an additional specification, by adding interaction $Quartile_d$ terms, as included in the message, into equation (1), we also compare heterogeneity of responses based on the pre-period percentile of service:

$$R_{fd} = \alpha + \beta_s Size_d + \beta_q Quartile_d + \gamma_1 Treat_d + \gamma_2 DirectEmail_d + \gamma_3\ DirectEmail_d * Treat_d + \gamma_{1q} Treat_d * Quartile_d + \gamma_{2d} DirectEmail_d * Quartile_d + \gamma_{3d}\ DirectEmail_d * Treat_d * Quartile_d + \varepsilon_{fd} \quad (2)$$

where the estimate of the parameter γ_1 corresponds to the average treatment effect of sending a treatment email directly to chairs and then the estimate of the parameter γ_{1q} corresponds to how the service quartile message changes the causal effect of receiving a treatment email directly to the chair. Similarly, the coefficient of the interaction of $Quartile_d$ with $DirectEmail_d * Treat_d$ corresponds to the estimate of how the quartile content of the email message sent directly to the faculty incrementally change responses, relative to the chair's causal effect by quartile estimated by γ_{1q}.

In a third specification we further interact all variables of interest and lower order terms with an indicator of whether the respondent is female. The equation to be estimated, similar to equations (1) and (2), estimates average and quartile specific treatment effects, but now distinguishes the effects by gender. The coefficients of interest, besides ($\gamma_1, \gamma_{1q}, \ \ldots, \ \gamma_3, \gamma_{3q},$) are ($\gamma_{1n}, \ldots, \gamma_{3n}$), the ones associated with the female indicator.

$$R_{fd} = \alpha + \beta_s Size_d + \beta_q Quartile_d + \gamma_1 Treat_d + \gamma_2 DirectEmail_d + \gamma_3\ DirectEmail_d * Treat_d + \gamma_{1q} Treat_d * Quartile_d + \gamma_{2d} DirectEmail_d * Quartile_d + \gamma_{3d}\ DirectEmail_d * Treat_d * Quartile_d + \delta\ Female_f + \cdots + \gamma_{1n} Treat_d * Female + \gamma_{3n}\ DirectEmail_d * Treat_d + \cdots + \varepsilon_{fd} \quad (3)$$

where all the interaction lower order terms are omitted to save space but are included in the regression specification (3).

A final specification is run by interacting a dummy variable for never having served before in committees, during their appointment at the university, with all the treatments and lower order terms. The resulting coefficients of interest correspond to how responses by those new to service depart from the average response rate overall and from the response rate by quartile and by direct email versus top-down email.

IV. Results

A. Response Summary Statistics

Overall, a total of 253 responses were obtained for the 2014 call. Compared to the previous year's 139 responses, this consisted of an 82% increase.[6] Table 5 breaks up responses and non-responses by Treated and by Control groups. In particular, we include all ranks of faculty in the data, given that we care about willingness to respond to the email call for service, not whether a faculty member can actually serve (given that the institution discourages assistant professors from actually serving until tenure, which means only associate professor or higher can serve). The summary statistics in Table 5 exclude all the observations originating from high service quartile departments and is organized as two separate panels. In the top panel, the total number of faculty that responded and the total number of faculty that did not respond are reported both for the groups of departments whose chair received a treated email (titled "Treated Chair Email Group") and for the groups of departments whose chair received a control email (titled "Control Group"). In the bottom panel we break up the reported summary statistics into the group whose faculty directly received a treatment email (titled "Direct Email Treated Group") and the group whose faculty received directly a control email (titled "Direct Email Control Group").

[6] While the aggregate data on department service goes back to 2005, we only have 2014 and 2013 response data at the faculty level since we were not able to gather historical panel response data for past years at the micro faculty level.

Table 5. Summary Statistics for Service Quartiles 1, 2, and 3, Excluding 4					
	Replied in 2014		Did not Reply in 2014		
					Total
Treated Chair Email Group	97	17%	477	83%	574
Control Group	89	14%	538	86%	627
Total	186		1015		1201
	Replied in 2014		Did not Reply in 2014		
					Total
Direct Email Treated Group	20	24%	65	76%	85
Direct Email Control Group	22	18%	102	82%	124
Total	42		167		209
Source: 2014 Call for service reply database.					

We find that the treated chair email group had an average response rate of 17% while the corresponding control group had a response rate of 14%. In terms of the faculty direct email treatment, on average, the response rate for the treatment group is about 24%, which is larger than the 18% response rate obtained in the corresponding control group.

Extending the analysis of the average reported response rates of Table 5, in Table 6 we report the average response rates by grouping the summary statistics of response rates by 2013th service quartiles of the departments of origin. The lowest service quartile is on top, middle in the middle panel, and the third service quartile is reported in the bottom of Table 6.

Table 6. Summary Statistics by Service Quartiles

Lowest Service quartile	Replied in 2014		Did not Reply in 2014		Total
Treated Chair Email Group	38	19%	162	81%	200
Control Group	23	9%	221	91%	244
Total	61		383		444

Second Service quartile	Replied in 2014		Did not Reply in 2014		Total
Treated Chair Email Group	37	16%	193	84%	230
Control Group	33	18%	151	82%	184
Total	70		344		414

Third Service quartile	Replied in 2014		Did not Reply in 2014		Total
Treated Chair Email Group	37	16%	193	84%	230
Control Group	33	18%	151	82%	184
Total	70		344		414

Highest Service quartile	Replied in 2014		Did not Reply in 2014		Total
Control Group	66	16%	347	84%	413
Total	66		347		413

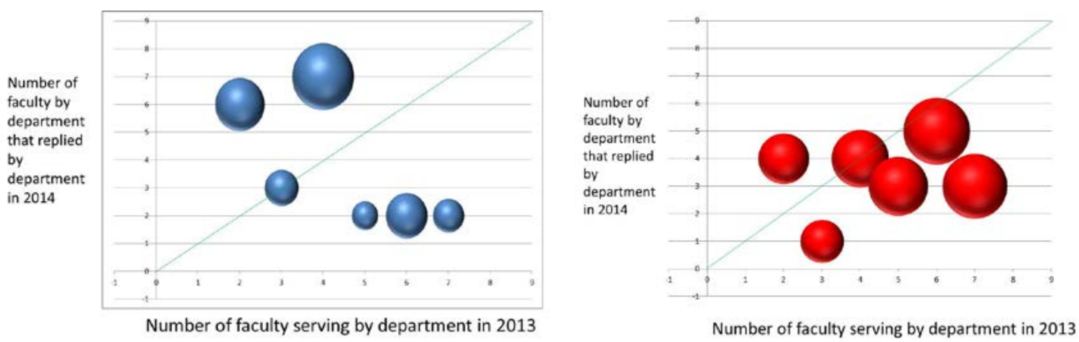
What we notice is that, for the lowest quartile, the treatment group response rate is twice as large as the response rate of the control group, while for the second and third quartiles the response rates for the treatment groups are smaller than the corresponding control group response rates.

A visual depiction of the replies by department given service in the previous year, for the direct email treatment and control group is given by Figure 1, and for the chair email treatment and control group in Figure 2. For both figures, on the x-axis we have the service by department in 2013, on the y-axis the number of faculty that replied by department in 2014, and each point size is a function of the department size represented by each dot. In blue on the left of Figure 1 and Figure 2, we have the control observations and in red on the right, the treated observations.

The dots above the 45 degree line (in green) are departments where there was an increase in service relative to the previous year.

Figure 1. Service in Pre-Period and Response to Direct Email to Faculty

(a) Control Departments **(b) Treated Departments**

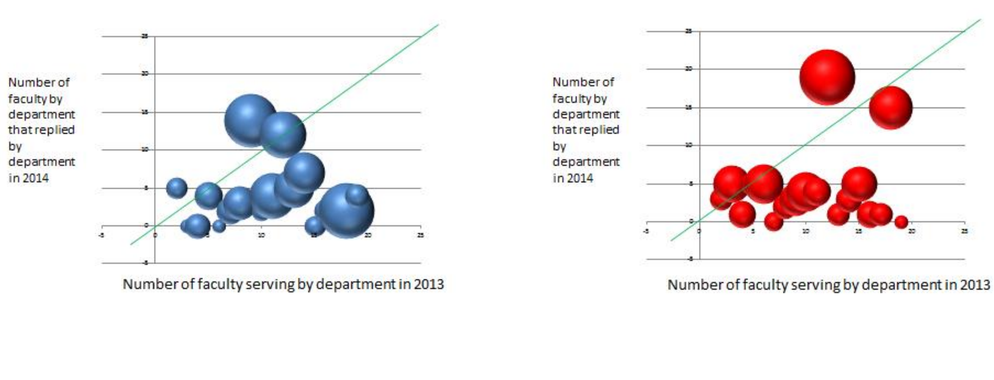


Control Departments are in Blue, Treated in Red, and dot size corresponds to the size of each department.

From the visual interpretation of Figure 1 we see that a direct email to faculty featuring the treatment message had a drop in service for larger departments, while in the control group, the direct email featuring no treatment message led to an increase in service from larger departments. This presents suggestive evidence that the treatment direct email did not have a positive average effect on service participation, which we will investigate formally in the regression analysis.

Figure 2. Service in Pre-Period and Response to Chair Email

(a) Control Departments **(b) Treated Departments**



Control Departments are in Blue, Treated in Red, and dot size corresponds to the size of each department.

Figure 2 suggests that while the chair email dropped service for most of the departments, a couple departments increase service responses relative to the previous years in the treatment and in the control group. Also, while larger departments increase service participation due to the treatment, and larger departments decrease participation in the control group. This is suggestive evidence that a chair email treatment effect could be positive, which we will analyze formally next.

B. Response Average Effects

While the above average patterns are indicative, we pursue a more formal analysis of the significance of the response rate changes caused by the different treatments in several regression specifications.

Table 7. Average Response to the Service Treatment Call				
Dependent Variable Replied2014=1 if a faculty member replied, =0 otherwise				
	Linear Prob Model	Linear Prob Model	Probit	Probit
Treated	0.0239	0.0238	0.1051	0.1055
	(0.03)	(0.03)	(0.15)	(0.14)
Direct Email	0.0442	0.0437	0.1861	0.1849
	(0.03)	(0.03)	(0.13)	(0.13)
Treated Direct Email	0.0312	0.0455	0.0897	0.1511
	(0.05)	(0.05)	(0.19)	(0.18)
Size		0.008		0.0352
		(0.01)		(0.06)
Service quartile		0.0137		0.0595
		(0.02)		(0.08)
Constant	0.1332***	0.0798	-1.1114***	-1.3466
	(0.02)	(0.05)	(0.11)	(0.25)
Number of Observations	1203	1203	1203	1203
R squared	0.01	0.01		
Log Likelihood	-479.910	-479.195	-515.099	-514.357
Standard errors in parentheses clustered at the department level				
* p<0.10, ** p<0.05, *** p<0.01				

Table 7 reports the average effects of the treatments of the regression specification (1). The dependent variable is equal to one if a faculty member in a certain department replied to the service call, and zero otherwise. In column 1 and 2 of Table 7 we report the estimates from a linear probability model, while in columns 3 and 4 we report estimates from a Probit model specification. In columns 1 and 3 we only include as independent variables the treatment indicators, defined in equation (1), while in columns 2 and 4 we also include controls for size and service quartile of the faculty member's department. In column 1, while average response rates are about 13%, the treated email and the Treated Direct email cause, respectively, a two and three percent increase in response rates, but those point estimates are not statistically different from zero, where all standard errors are clustered at the department level. In the other columns results are unchanged and are very consistent in that we estimate no significant average changes in response rates caused by the chair treatment as well as by the direct faculty email treatment.

However, as we report in table 8, interacting the treatments with the service quartile featured in the message, yields very interesting and significant causal responses. The first two columns have as dependent variable an indicator equal to one if a faculty member replied in 2014 and equal to zero otherwise. As independent variables these two columns feature all the interactions of interest and also include department size and service quartile as controls. Column 1 corresponds to the linear probability model and column 2 corresponds to the Probit model. Then, column 3 repeats the same probit specification in column 2, with the same independent variable, but now the dependent variable is equal to one if a faculty member responded in 2014 but had not responded to the 2013 call of service (that was sent the previous year) and is equal to zero otherwise. Column 3 investigates the effect of the treatments, therefore, on respondents to the call for service only in 2014—that is, faculty that replied in 2014 and did not reply in 2013 to the call to service. Note that this group of faculty, under the column header "Replied 2014 only", could have served before 2013. One action is replying, the other action is serving. Here, we investigate heterogeneity of responding to the call for service when you did not respond in the previous year—we do not identify yet the heterogeneity in serving for the first time or not. Later, in the final tables in this paper, we will estimate a specification distinguishing faculty by being "new to service".

Finally, columns 4 and 5 replicate the specifications in columns 2 and 3, but replace the linear $Quartile_d$ variable (and its interactions) with a dummy variable for a department being in the lowest service quartile. Evidence from Table 6 indicates that the effect of rank is non-linear. In particular, we saw that for the lowest quartile, the treatment group response rate is twice as large as the response rate of the control group, while for the second and third quartiles the response rates for the treatment groups are smaller than the corresponding control group response rates. For this reason, in columns 4 and 5 we investigate whether the treatment effects are different for the departments in the lowest service quartile.

Table 8. Heterogeneous Responses to the Service Treatment Call by Service Quartile					
	Linear Prob Model	Probit	Probit	Probit	Probit
	Replied2014	Replied2014	Replied 2014 Only	Replied 2014	Replied 2014 Only
Treated	0.1378	0.6107	0.046*	-0.0796	-0.0077
	(0.09)	(0.39)	(0.03)	(0.13)	(0.13)
Direct Email	-0.0191	-0.0409	-0.0239	0.1277	0.0321
	(0.07)	(0.36)	(0.06)	(0.13)	(0.12)
Treated Direct Email	0.0161	0.0516	-0.0061	0.3617**	0.3253**
	(0.12)	(0.51)	(0.07)	(0.15)	(0.16)
Treated * quartile	-0.0589	-0.2601	-0.0267*		
	(0.04)	(0.16)	(0.02)		
Direct Email* quartile	0.0262	0.0893	0.0242		
	(0.03)	(0.15)	(0.03)		
Treated* direct email * quartile	0.0259	0.0928	0.0041		
	(0.05)	(0.21)	(0.03)		
Service quartile	0.0338	0.1576	0.0255*		
	(0.03)	(0.13)	(0.01)		
Lowest Service quartile dummy (LSQD)				-0.3559	-0.2238
				(0.24)	(0.21)
Treated*LSQD				0.5089*	0.4247
				(0.31)	(0.30)
Direct email * LSQD				-0.0598	-0.2246
				(0.26)	(0.23)
Treated*direct email* LSQD				-0.2745	0.094
				(0.36)	(0.36)
Size	0.0125	0.0538	-0.0002	0.0488	0.0729
	(0.01)	(0.05)	(0.01)	(0.05)	(0.05)
Constant	0.0269	-1.601***	-0.0131	-1.1400***	-1.4474***
	(0.07)	(0.33)	(0.03)	(0.22)	(0.20)
Observations	1203	1203	1203	1203	1203
R squared	0.0107				
Log Likelihood	-476.5659	-511.7031	301.1283	-510.7127	-429.0065
Standard errors in parentheses clustered at the department level		* p<0.10, ** p<0.05, *** p<0.01			

In column 1 and 2, sending the treated email to the chairs, or a treated direct email to faculty, does not cause participation to increase significantly, as can be seen by the positive and not significant point estimates associated with the indicators "Treated" and "Treated Direct Email". However, sending a treated email to the chairs causes an increase in terms of new service replies, as can be seen in the positive and significant estimate in column 3. Moreover, the higher the quartile featured in the email sent to chairs for new service replies, the lower the estimated treatment effect, as can be seen in the negative and significant estimated coefficient associated with the interaction of "Treated and Quartile" in column 3. In contrast, the direct email to faculty causes no significant average changes in response rates, nor does the different quartile message included in the direct email to faculty cause different effects on response rates. In summary of the first three columns, there is no effect on overall response rates (columns 1 and 2) but there is an effect on new replies to service (column 3).

Turning to the last two columns, when using the lowest service quartile dummy we find a positive and significant direct treatment effect for those not in the lowest service quartile, as evidenced by the coefficients on "Treated Direct Email". We also find the treatment effect is largest for those in the lowest quartile, with a positive and significant estimate for "Treated*LSQD", while being in the lowest quartile without treatment does not produce a significant effects, with a negative but non-significant estimate on "LSQD". Finally, receiving a direct email does not produce an additional increase in response rates for those treated in the lowest service quartile, as evidenced by the non-significant estimate on "Treated*Direct Email*LSQD". Thus, columns 4 and 5 indicate that the effect of rank is non-linear, with the lowest service quartile responding more to the treated chair email and the middle service quartile groups responding to the treated direct emails.

C. Gender Differences in Responses

An interesting heterogeneity analysis pertains to gender differences in responses to the treatments. In Table 9, with the same rows as columns 1 to 3 in Table 8, we break up the sample so that the average effect for women is in the first two columns and for men is in the last two columns.

Table 9. Women and Men Responses to the Service Treatment Call by Service Quartile				
	Linear Prob Model- Women	Probit- Women	Linear Prob Model- Men	Probit- Men
	Replied2014	Replied2014	Replied2014	Replied2014
Treated	-0.001	0.0603	0.183*	0.799*
	(0.14)	(0.64)	(0.10)	(0.46)
Direct Email	0.0431	0.2591	-0.0309	-0.0981
	(0.17)	(0.81)	(0.09)	(0.46)
Treated Direct Email	0.0147	-0.1195	0.0653	0.1496
	(0.24)	(1.25)	(0.15)	(0.62)
Treated * quartile	0.0159	0.0333	-0.084*	-0.371*
	(0.06)	(0.27)	(0.04)	(0.19)
Direct Email* quartile	0.0107	0.0078	0.0256	0.0909
	(0.07)	(0.31)	(0.04)	(0.20)
Treated* direct email * quartile	-0.0605	-0.1651	0.0319	0.148
	(0.11)	(0.59)	(0.06)	(0.26)
Size	0.023	0.1153	0.008	0.0339
	(0.02)	(0.10)	(0.02)	(0.07)
Service quartile	0.0474	0.236*	0.0301	0.1387
	(0.03)	(0.13)	(0.03)	(0.15)
Constant	-0.0433	-2.01***	0.0527	-1.479***
	(0.09)	(0.44)	(0.08)	(0.41)
Observations	336	336	870	870
R squared	0.0221		0.0192	
Log Likelihood	-117.2433	-132.2801	-352.5252	-374.2457

Standard errors in parentheses clsutered at the Dept Level . * p<0.10, ** p<0.05, *** p<0.01

We do find gender differences in uptake when revealing peer information, in that the average effect is driven by the significant response of men, while women do not respond significantly to any of the treatments. We can see this in comparing the non-significant coefficients in the first two columns with the significant coefficients in the last two columns associated with the row labeled “Treated” and Treated*quartile.”

Looking at the control group allows us to relate our findings to previous research that analyzed gender differences in standard calls for voluntary service without any peer information intervention, such as Vesterlund, et al. (2015), and the results are in Table 10. We do not find that females respond significantly more than men to the general call for service.

Table 10. Response of Control Group by Characteristics		
Dependent Variable Replied2014=1 if a faculty member replied, =0 ow.		
	Linear Prob Model	Probit
female	-0.0139	-0.0653
	(0.03)	(0.15)
Size	-0.0046	-0.0191
	(0.02)	(0.10)
Service quartile	0.0298	0.1399
	(0.02)	(0.12)
Constant	0.098	-1.294***
	(0.08)	(0.39)
Number of Observations	502	502
R squared	0.01	
Log Likelihood	-169.259	-195.642
Standard errors in parentheses clsutered at the Dept Level . * p<0.10, ** p<0.05, *** p<0.01		

On one hand, men react to information that they are serving more than their peers by decreasing their service, and this change might be caused either by decreased guilt or by men making a Bayesian inference that they are missing out and being free ridden by other peers, since they could be spending their faculty time in research. On the other hand, women do not exhibit behavior consistent with this strategic response. Our findings are consistent with women being less motivated by peer information than men, when responding to service calls. Our results are also consistent with women being more informed than men about other comparable department’s service participation, as well as women having no more margin to increase service because the participation is already capped (Misra et al, 2011). Future work could consider expanding the design to test which one of the reasons lies behind the gender differences in service responses to peer information.

From Table 10, it is also interesting to note that, absent the peer information treatments, we find that the typical control group response is such that faculty from departments with the higher levels of historical service are the ones who are more likely to respond to the appeal to voluntary service, given the positive and significant point estimate in the row "Service quartile", perpetuating the representation of those departments in governance.

D. Treatment effects in terms of New Service Responses

In specification (3) we finally investigate heterogeneity of responses in terms of faculty old and new to service. The results from this specification are reported in Table 11. To be clear, when a faculty member replies and volunteers to serve, a faculty member may be taken up on the offer or not. We define an indicator called "New to Service" as being equal to one if the faculty member has never served in the university during their appointment, according to the university file of each faculty, and is equal to zero otherwise. We then interact the treatment indicators with this variable to distinguish the response rate changes caused by the treatments for faculty that have served before and for those that have never served. Furthermore, we report point estimates of the changes in response rates for two kinds of variables as dependent variables. In column 1 of Table 11 we have a variable as dependent variable that is equal to one if a faculty member replied in the past in 2013 as well as replied in 2014. In column 2 the dependent variable is equal to one if a faculty member replied and equal to zero otherwise. Column 1 investigates changes in response rates for faculty that have recently responded to the call while column 2 investigates changes in overall response rates.[7]

[7] Note that responding does not mean necessarily that you get to serve, so it is possible to be new to service and always to respond to calls to service.

Table 11. Heterogeneous Responses to the Service Treatment Call by New or Old Service		
	Replied in 2013 and 2014	Replied in 2014
Treated	0.0404	-0.0161
	(0.03)	(0.05)
Direct Email	-0.0254	-0.0575
	(0.05)	(0.06)
Treated Direct Email	0.0002	0.004
	(0.06)	(0.10)
Treated * quartile	-0.0214	-0.0048
	(0.01)	(0.02)
Direct Email* quartile	0.0271	0.0396
	(0.03)	(0.03)
Treated* direct email * quartile	-0.0163	0.0241
	(0.03)	(0.04)
Service quartile	0.0184*	-0.0018
	(0.01)	(0.02)
Treated * New to Service	0.0326	0.94***
	(0.09)	(0.02)
Treated Direct email * New to Service	0.0096	0.0644
	(0.24)	(0.15)
Quartile * New to service	0.0852**	0.4036***
	(0.24)	(0.15)
Treat* Quartile* New To Service	-0.0585	-0.396***
	(0.07)	(0.04)
Treat Direct email* Quartile* New To Service	0.1093	-0.068***
	(0.09)	(0.02)
Constant	-0.0138	0.054
	(0.03)	(0.05)
Observations	1203	1203
R squared	0.0676	0.5978
Log Likelihood	334.4984	64.7474
Standard errors in parentheses clustered at Dept level	* p<0.10, ** p<0.05, *** p<0.01	

The results are quite interesting. Looking at column 1 first we focus on responses of faculty who recently responded to the call to service. The average effect of sending an email to the chair (in the "Treated" row) is as expected not significant on causing changes in response rates for faculty. Second, the estimated effect is also not statistically different for faculty who are defined as new to service (the interaction "Treated*New To Service"). Third, among the faculty new to service and responding for the first time in 2014, the chair email causes a significant and positive effect in the row “Treated *New To Service”. However, the direct email has no additional incremental effect beyond the chair effect as can be seen in the insignificant coefficient of the interaction “Treated Direct email*New To Service” in column 2.

Looking now at the bottom of Table 11, we find that disclosing service quartiles in the chair message causes no significant increases in responses from faculty that had previously served (which corresponds to the coefficient on the interaction “Treated*Quartile”). Interestingly, it is for the faculty who would be new to service, that the higher the featured service quartile in the email sent to the chair that causes them to respond less to the call, which can be seen in the negative and significant coefficient associated with the interaction “Treat* Quartile*New to Service” for the people responding for the first time in 2014. Anecdotal evidence indeed suggested that departments became quite nervous when receiving a low service quartile ranking in the email to the chair. The administrative analyst who sent out the emails received several chair replies to the treatments, especially from chairs who were alarmed about their departments’ low rankings. Some chairs informed this analyst that they would definitely reach out to their faculty to serve, focusing especially on faculty who had not previously done so.

Turning now to disclosing quartiles in the direct email, the “Treat Direct email* Quartile* New To Service” coefficient for the people responding only in 2014 is negative and significant—disclosing a higher ranking of service leads to less new service responses due to the chairs email and also in addition due to the direct email. Interestingly, this is the first time the treatment of sending a direct email to faculty caused any significant effect on response rates of faculty. *Finally*, the positive and significant coefficients on “Quartile*New To Service” suggests that faculty in control departments that are new to service respond more the higher the quartile of the department, even though they are not treated and their quartile is not revealed to them.

V. Conclusions

In this paper we provide a first step towards understanding if releasing information about service participation rankings affects the behavior of those offering to serve. Using a randomized information disclosure intervention we are able to measure the effect of individually disclosing peer rankings of service on the probability of its members to respond to a call to service. The results are promising and interesting, shedding light into possible behavioral mechanisms consistent with incentives behind voluntary service provision.

We find that revealing low rankings (in the form of lowest service quartiles among peers) leads to significantly higher response rates than disclosing high service rankings. Moreover, beyond pursuing a top down service call, by informing the head of a department, sending a direct email to individuals does not have a significant incremental effect on average voluntary service responses. Interestingly, however, disclosing that the unit is among a higher serving quartile discourages new service both in the chair treatment as well as in the additional direct email treatment. The direct member treatment causes significantly higher new service responses than the treatment aimed at the head of the unit. This means that people who previously did not respond to the call to serve sent to the head of the unit, are induced to change their behavior less when receiving, in addition, a direct solicitation informing them that their department is already serving a lot, compared to their peers.

In our gender heterogeneity analysis, we extend the findings in Vesterlund et al. (2015). In contrast to that paper, we do not find that receiving a call to service (without any treatment) leads to more replies by women. Interestingly, we estimate there to be gender differences in the response to service calls via peer effects by men, not women. In particular, we estimate that men, when asked directly by a chair and when revealed with peer rankings, do respond more than women to service calls.

This is the first paper to examine specifically whether willingness to serve is influenced by internal service rankings. Future work could consider making the department specific disclosed information not only available to each particular unit, as in this paper's design, but rather could consider making the information public and available to all units. This could be done in the form of a disclosed service performance "Top Service" lists. Additional investigations could test whether results are heterogeneous along other dimensions such as age or how long someone has worked at the institution.

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Appendix

Treatment and Control Messages in Email

Control Email: Dear Chair. Thank you for the service your department has given to campus! We remind you all to complete the call for service for the year 2014-15 by following the link below and sending this email to your faculty …

Treatment Email : Dear Chair, Thank you for the service your department has given to campus! Given data on 64 departments and compared to your peer departments of similar size you are among the *second quartile (25-50th percentile) (*) in terms of service participation in 2013 and 2014*. We would like to encourage you and your faculty to respond to the service call and have your department have a stronger voice on campus governance. We remind you all to complete the call for service for the year 2014-15 by following the link below and sending this email to your faculty …

(*) the blue text would vary between

- ***"lowest first quartile (25th percentile)",***
- ***"second lowest (between 25th and 50th percentile)/ or below median"***
- ***and "around median" (for those in 50-75 th percentile) .***