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Empirical Analysis of STEM Faculty Productivity: Using NbClust and Logistic Regression to Explore Interactions Among Faculty Teaching and Research Productivity Metrics, Demographic, and Disciplinary Characteristics

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Abstract

This study investigates the nexus between research and teaching productivity among STEM faculty at a public research-intensive university, analyzing data from 553 faculty members across four STEM disciplines: Biological Sciences, Engineering, Information and Computer Sciences, and Physical Sciences. Through the combined application of cluster analysis using the NbClust package and logistic regression, the research explores the correlation between productivity metrics and faculty demographics, including position type, rank, gender, and discipline. The analysis reveals distinct productivity clusters characterized by varying levels of research and teaching productivity outcomes across demographic groups, underscoring significant disparities. The findings emphasize the imperative for institutional policies that holistically support both teaching and research to foster faculty success. By offering a nuanced understanding of faculty productivity profiles, this study informs strategies for equitable resource allocation, faculty development, and evaluation, ultimately contributing to the advancement of STEM education and the fulfillment of institutional missions.

Keywords: teaching-research productivity nexus, NbClust package, cluster analysis, logistic regression, STEM Education

INTRODUCTION

Faculty in higher education contribute to various activities, including research, teaching, public and campus service, and administration (Link et al., 2008). Despite the diversity of these responsibilities, research productivity—often measured through grant awards and publications—remains the primary metric for evaluating faculty success at the research university (Schimanski & Alperin, 2018; Cadez et al., 2017). Research-intensive (R1) universities, as defined by the Carnegie Classification system, prioritize the strength of one's research program while giving less weight to teaching excellence and service (Robert & Carlson, 2017). However, even at a research-intensive university, teaching remains an essential part of the institution's mission. For decades, administrators like former University of California President Clark Kerr have warned that an overemphasis on research could lead to neglecting undergraduate education (Kerr, 2001) and that faculty value might become tied solely to their ability to secure research funds rather than their teaching capabilities (Kerr, 2001; Lapworth, 2004; Elen et al., 2007). In response, many research-intensive universities have increasingly relied on lecturers to fulfill their teaching missions, especially given rising college enrollments and shrinking campus budgets (Bampton, 2017; Stenerson et al., 2010). Lecturers, typically employed part-time or on a temporary basis, are non-tenured faculty whose responsibilities are almost exclusively focused on teaching obligations (Kezar & Maxey, 2014). This strategic reliance has created distinct groups of faculty dedicated to research or teaching, highlighting the need for a more efficient approach to ensure both missions are adequately supported and remain connected.

Recently, universities have begun to leverage another class of faculty, the teaching-focused faculty. These faculty spend most of their time on classroom instruction, but unlike lecturers, they also have scholarly and/or service responsibilities (Rawn & Fox, 2018; Harlow et al., 2020; 2022). Despite the increasing prevalence of teaching-focused faculty positions within academia, there remains a limited understanding of the contributions of these faculty relative to traditional, research-focused, tenure-track faculty and lecturers in the context of the research-intensive university mission. Related to this, research and teaching productivity have primarily been examined in the context of these latter two, more common, faculty positions (i.e., research-focused faculty and lecturers). For example, existing literature has quantified the impact of contingent faculty on student academic performance, a key point of convergence between tenure-track roles and contingent faculty positions (Figlio et al., 2015; Xu & Solanki, 2020). However, the introduction of teaching-focused positions that often incorporate research duties, and the growth of discipline-based education research fields has complicated the definition of faculty success (Rawn & Fox, 2018; Harlow et al., 2020). This shift in the academic landscape highlights the need to reevaluate success metrics as the academic community begins to navigate the increasingly blurred line between teaching and research productivity. Additionally, while there have been efforts to measure productivity in both domains, methodologies are varied, with no universally accepted standards for evaluating teaching and research productivity (Prince et al., 2007).

This complex balance between teaching and research is particularly pronounced in science, technology, engineering, and mathematics (STEM) programs. STEM faculty have access to significant external funding opportunities with research tied to multi-billion-dollar industries (Gibbs et al., 2014). But STEM fields have also been plagued by persistent inequities, with individuals from minoritized populations often experiencing lower levels of success in STEM higher education programs and careers (Casad et al., 2021; Blackwell et al., 2009; White-Lewis et al., 2022). As STEM faculty consider these responsibilities, the crucial interplay between teaching and research impacts institution-wide discussions regarding limited resources in terms of funding, personnel, and space (Brennan et al., 2019; Healey, 2005). Thus, establishing a constructive relationship between research and teaching is critical for optimizing university funding and operational effectiveness (Healey & Jenkins, 2005) and addressing gaps in prior research could provide valuable insights for university administrators and higher education researchers to better support faculty development and student success (Deem & Lucas, 2006).

In this paper, we explore the interactions between metrics representing research and teaching productivity and how they correlate with STEM faculty demographics, such as position type, position rank, gender, and discipline. We focus on faculty affiliated with one of the campuses of the University of California (UC) since, within the UC system, they employ three primary categories of full-time faculty: research-focused faculty, lecturers, and a growing class of tenure-track, teaching-focused faculty (Harlow et al., 2020; Harlow et al., 2022; Rozhenkova et al., 2024). This study aims to deepen our understanding of research and teaching productivity and offer recommendations to administrators for resource allocation, faculty development, and recruitment and retention strategies by analyzing a set of teaching and research productivity metrics. More specifically, our research questions (RQs) are:

1. How are research and teaching productivity interrelated?
2. To what extent do faculty vary in terms of their research and teaching productivity metrics?
3. How do faculty characteristics (*faculty type, tenure-status, discipline, and gender*) relate to the observed teaching and research productivity?

LITERATURE REVIEW

Research and Teaching Productivity

Faculty productivity is generally divided into research and teaching metrics, and there is not a universally accepted way to measure each (Marsh & Hattie, 2002). For research productivity, common indicators include the volume of peer-reviewed journal publications, the journal's impact factor, and the number of times these publications are cited. These criteria capture a researcher's influence and the dissemination of their work within the scholarly community (Bak & Kim, 2015). Additionally, acquiring external grant funding is a key measure, highlighting a researcher's competitiveness in securing financial support and the perceived merit and viability of their work (Fairweather, 2002). Furthermore, participation in conferences and workshops is recognized as part of a faculty's research output (Fairweather, 2002; Webber et al., 2013). Together, these metrics seek to offer a holistic view of a researcher's contributions, although there are ongoing debates over the emphasis on quantity versus quality of academic work (Marsh & Hattie, 2002; Griffiths, 2004).

For teaching productivity, one common metric is the number of classroom-contact-hours as a tangible metric of teaching commitment (Fairweather, 2002, 2005; Santo et al., 2009; Webber et al., 2013). Additionally, student evaluations of teaching have been widely used (Balam & Shannon, 2010; Bedggood & Donovan, 2012; Uttl et al., 2017; Zabaleta, 2007; Penny, 2003; Webber et al., 2013), as they provide direct feedback on instructor effectiveness, clarity, and engagement from the learner's perspective despite debates over their reliability and bias (Marsh & Hattie, 2002). Other methods include assessing achievement of student learning outcomes, such as grades or performance on standardized assessments, to gauge the impact of instruction on student achievement (Palali et al., 2018). However, there is still considerable debate as to whether these measurement metrics effectively capture the essence of teaching productivity (Benton & Cashin, 2014).

Research and Teaching Productivity Nexus

Perspectives on the relationship between faculty research and teaching productivity vary widely. Some scholars argue that research and teaching reinforce each other, with activities in one domain enriching and supporting the other (Cadez et al., 2017; Galbraith & Merrill, 2012; Schapper & Mayson, 2010; Becker & Kennedy, 2005). Conversely, others caution that an intense focus on research may detract from teaching productivity, with research achievements overshadowing the importance of undergraduate education (Jonker & Hicks, 2014; Waltman et al., 2012). Fairweather (2002) notes that prioritizing one area often reduces attention to the other, while Winslow (2010) found that research could marginally improve teaching effectiveness, particularly in research-intensive settings. Xu and Solanki (2020) and Keller et al. (2017) argue that integrating research into teaching enhances pedagogical knowledge, as evidenced by improved student outcomes and curriculum integration. Conversely, some propose that teaching and research productivity are distinct activities, meaning success in one doesn't necessarily impact success in the other (Figlio & Schapiro, 2017; Marsh & Hattie, 2002). Hattie and Marsh's study (2002) identified almost no correlation between the two activities, suggesting that they operate independently. Morales and colleagues (2017) found that the independent research supervision of undergraduate students was related to faculty's h-index (i.e., a measure of the productivity and impact of a researcher based on their most cited papers) and funding, reflecting a contribution to training future academics as beneficial to research productivity. These mixed findings highlight the complex dynamics between teaching and research and emphasize the need to consider which teaching and research productivity-related variables or methodologies are utilized, along with the impacts of faculty roles and demographics when evaluating productivity.

Research and Teaching Productivity in the Context of Faculty Demographics

Type and Rank. In the diverse landscape of higher education, faculty position types such as lecturers, research faculty (RF), and teaching faculty (TF) each carry distinct responsibilities and expectations that significantly influence their productivity and contribution to higher education institutions. Lecturers primarily teach and are judged almost exclusively by their instructional efforts rather than their research (Beth & Lee, 2020). RF, however, are mostly evaluated and rewarded based on their research program, signaling a clear preference for research over teaching in research-intensive institutions (Brew, 2010). TF are expected to prioritize quality education alongside their research and service work (Bush et al., 2011; Harlow et al., 2022; Healey et al., 2016; Prince et al., 2007). Despite these defined roles, the reality of teaching and research activities in the context of these position types is more complex. LEC, tenure-track TF, and tenure-track RF often cross into each other's domains, showing that an empirical approach is necessary to capture their contributions accurately.

Faculty rank (assistant, associate, full) also deeply affects roles and responsibilities (Beth & Lee, 2020; Scott & Danley-Scott, 2015). Not-yet-tenured faculty (assistant professors) are under significant pressure to establish their research programs while balancing these demands with new teaching assignments (Hesli & Lee, 2013; Monroe et al., 2008). Achieving tenure (associate, full professors), provides faculty with enhanced job stability and the liberty to pursue more speculative and long-term research endeavors, while often coming with increased service expectations (Singh & Stoloff, 2003). For lecturers, while it may be possible to receive longer-term contracts that can resemble a tenured status (Bolitzer, 2019), their expectations often do not change throughout the progression of their careers and are marked by consistent teaching assignments (Shayne, 2019). These points emphasize the dynamic and multifaceted nature of academic roles, where different faculty ranks can introduce both opportunities and challenges regarding the intricate balance between research and teaching demands.

Gender. The academic community has long debated gender disparities in faculty productivity. Historically, work has found that female faculty often experience lower research productivity and heavier teaching loads compared to males (Astin & Davis, 2019; Santo et al., 2009; Xu, 2008; Maphalala & Mpofu, 2017; Maske et al., 2003). Factors such as unequal access to resources, fewer opportunities for research funding, and higher service demands have been cited as significant contributors to these disparities (West & Curtis, 2006; Misra et al., 2012; Boring & Ottoboni., 2016). Conversely, recent studies argue that gender differences in productivity largely disappear when adjustments are made for variables such as discipline, tenure-status, and family commitments (Ceci & Williams, 2011; Fox, 2005). For instance, research by Ginther et al. (2011) finds no substantial gender-based differences in grant funding success rates when review processes are structured to minimize bias. Marschke et al. (2007) similarly report that teaching loads are comparably distributed among genders once rank and departmental context are considered. Still, these continued debates indicate a need for additional empirical research to examine the presence of gender disparities in faculty academic productivity.

Discipline. Studies have shown that productivity metrics vary across disciplines due to differing publication norms, funding opportunities, and teaching demands (Sinha et al., 2013). For instance, faculty in STEM typically exhibit higher publication rates and greater access to funding, whereas humanities scholars often engage in projects like books that are not adequately captured by conventional productivity metrics (Lee & Bozeman, 2005). Additionally, teaching loads can vary dramatically; faculty in science and engineering might have lighter teaching responsibilities but heavier research obligations, in contrast to their peers in the humanities or social sciences, who often face greater teaching demands (Shin & Cummings, 2010). Even within STEM disciplines, there can be significant variability in how one measures productivity from field to field. Numerous studies have found that publication rates vary among STEM fields

(Dietz & Bozeman, 2005; Pinheiro et al., 2014; Lee, 2024). Dietz and Bozeman (2005) also saw that the rate of securing patents, which is not a metric commonly used in productivity studies, varies by STEM field and does not correlate with publication rate. Additionally, faculty who engage in interdisciplinary work, while beneficial for pushing forward cutting-edge research, may be penalized by traditional research metrics, as discipline-spanning work may be limited in terms of the number of journals willing to publish it (Leahey et al., 2017). These discrepancies underline the shortcomings of existing evaluative frameworks, which often fail to reflect the distinct characteristics of each discipline (Fairweather, 2002).

METHODS

Data

This study utilized data from 553 full-time STEM faculty employed at a single UC institution (a public, research-intensive institution in the western United States) between 2011 and 2017. These faculty were associated with one of four STEM units: School of Biological Sciences, School of Engineering, School of Information and Computer Sciences, School of Physical Sciences. The data related to faculty research productivity were collected from SciVal, Elsevier's research performance benchmarking tool (Elsevier, 2024), to better understand the impacts of research publications and from institutional data on external grant funding. The data related to teaching productivity were obtained from the institutional data of faculty-level records for all courses offered during the study period. Exclusion criteria were as follows: (1) part-time faculty, (2) faculty who had no research productivity during the study period, and (3) faculty who did not teach in any term during the study period.

Faculty Demographics

Faculty demographic data include faculty type (e.g., lecture, RF, TF), faculty rank (non-continuing, continuing, assistant, associate, full), discipline (Biological Sciences, Engineering, Information and Computer Sciences, Physical Sciences), and gender. There are two ranks that a lecturer may have: non-continuing (lecturers who have not yet achieved continuing status) and continuing (lecturers who have been employed for at least six years and have met specific benchmarks that enable longer-term contracts). For RF and TF, there are three ranks (assistant, associate, full). In addition to faculty rank, we created a new field 'Faculty Tenure-Status' to compare lecturer ranks (non-continuing, continuing) and research and TF ranks (assistant, associate, full). Since lecturers with continuing status are awarded six-year contracts that are almost always renewed, we treated this status as equivalent to tenure, otherwise considered as non-tenure. For TF and RF ranks, the faculty tenure-status for assistant rank is not-yet-tenured and for associate and full is tenured.

A significant portion of the faculty were RF (*n*=486; 88%) and a smaller portion were lecturers (*n*=33; 6%) and TF (*n*=34; 6%) (Table 1). Regarding faculty rank, most research and teaching professors were at full professor status (*n*=296; 54%), followed by assistant professors (*n*=133; 24%), and associate professors (*n*=91; 16%). Non-continuing lecturers (*n*=22; 4%), and continuing lecturers (*n*=11; 2%) made up a small fraction of the sample. In terms of discipline, the School of Biological Sciences had no lecturers, however, 23% of RF (*n*=113) and 41% of TF (*n*=14) were affiliated with this school. The School of Engineering had 26% of the RF (*n*=124) and 9% of the TF (*n*=3). The School of Information and Computer Sciences featured 12 lecturers (36%), 81 RF (17%), and 15% of the TF (*n*=5). The School of Physical Sciences had the highest number of lecturers (*n*=18; 55%) and RF (*n*=168; 35%) and the second-highest number of TF (*n*=12; 35%).

[Table 1]

Additional demographic data, presented in Table 2, highlight that the majority of faculty across all disciplines were male (Females=133, 24%; Males=420, 76%)

[Table 2]

During the study period, we measured eight teaching productivity metrics (total number of lower-division (LD) and upper-division (UD) undergraduate courses, undergraduate independent research (IR) courses, and graduate (GR) courses taught, and the average number of students enrolled in each of those course sections) and eight research productivity metrics (average citation count, citations per work, field-adjusted citation influence, h-index, production in the highest decile of citation rankings, publications ranked in the top decile of journals based on cite score, total scholarly contributions, and the overall research grants received). The definition of each metric, including the data source and related summary statistics can be found as supplemental materials (Appendices A, B).

Data Transformation and Standardization

Given the significant skewness in the distribution of each of the teaching and research productivity attributes, it was necessary to transform the data prior to analysis. We first applied a logarithmic transformation ($\log(x + 0.5)$) and then we standardized the log-transformed values using the formula:

$$z = \frac{\log(x + 0.5) - mean(\log(x + 0.5))}{standard\ deviation\ (\log(x + 0.5))}$$

so that each of the standardized teaching and research productivity attributes would have a mean of zero and a standard deviation of one. This process ensures that attributes with broader ranges do not disproportionately affect the calculation of the correlation matrix and the distance metrics during the cluster data analysis (Kandel et al, 2012).

Data Analysis

RQ1: How are research and teaching productivity interrelated?

We examined the correlation matrix between the standardized research and teaching productivity metrics to answer RQ1. First, we looked at the correlation within the standardized research metrics. Second, we looked at the correlation within the standardized teaching metrics. Lastly, we examined the correlations between the standardized research and teaching productivity metrics.

RQ2: To what extent do faculty vary in terms of their research and teaching productivity metrics?

We categorized faculty in clusters of similar research and teaching productivity metrics to address RQ2. Cluster analysis allows us to create similar groups of faculty within clusters while maintaining distinct differences between clusters (Kandel et al., 2012). The NbClust package in R (Charrad et al., 2014) was used to estimate the optimal number of clusters of faculty based on standardized research and teaching productivity metrics. For this study, we utilized hierarchical clustering with the complete linkage method and evaluated 30 different clustering indices to find the optimal number of clusters in our data. While the number of clusters is not predetermined, following the cluster analysis, we compared the standardized with the transformation values of the research and teaching productivity metrics across the resultant clusters using analysis of variance (ANOVA) and the Kruskal-Wallis tests (Jamil & Khanam, 2024; Ostertagova et al., 2014). The ANOVA and Kruskal-Wallis test for differences across the resultant clusters for each standardized with the transformation research and teaching productivity metrics and validate the heterogeneity across the resultant clusters.

RQ3: How do faculty characteristics (faculty type, tenure-status, discipline, and gender) relate to the observed teaching and research productivity?

Following the cluster analysis, we used the resultant clusters to compare faculty characteristics to the odds of falling into a particular resultant cluster using logistic regression (Hosmer & Lemeshow, 2013, Bhattacharjee & Karade, 2018). For each of the resultant clusters, a separate logistic regression model was carried out. The predictor variables include faculty type (lecturers, TF, RF), tenure-status (non-tenured, tenured), discipline (Biological Sciences, Engineering, Information and Computer Sciences, Physical Sciences), and gender (female and male). The response variable is whether the faculty is in the resultant cluster. The model is given by:

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k$$

For each categorical variable, we defined a reference group (RG) as the most prevalent group for each. For faculty type, the RG is RF. For tenure-status, the RG is tenured faculty. For discipline, the RG is the School of Biological Sciences. For gender, the RG is female faculty.

RESULTS

RQ1: How do research and teaching productivity metrics interrelate?

The correlation matrix (Table 3) reveals the relationships among the eight research productivity metrics. The analysis shows high positive correlations across most metrics, indicating strong interrelationships. Notably, “Average citation count” exhibits a strong correlation with both “Average citation per publication” (r=0.948) and “Average h-index”

(r=0.899), suggesting that increases in average citation count are associated with higher average citations per publication and a higher h-index. Similarly, "Average field weighted citation impact" is highly correlated with "Average citation count" (r=0.890) and "Average citation per publication" (r=0.912), indicating a close relationship between these metrics. The "Average scholarly outcome" shows a strong correlation with the "Average h-index" (r=0.855), implying a significant association between the two metrics. In contrast, the correlations involving "Sum of grant awards" are more moderate, with the highest being with "Average scholarly outcome" (r=0.477), indicating that faculty with higher amounts of grant dollars also tend to have higher scholarly output. Overall, the matrix underscores the interconnectedness of these research productivity metrics, with citation-related measures demonstrating the strongest correlations.

[Table 3]

The correlation matrix in Table 4 presents the relationships among eight teaching productivity metrics. The analysis reveals several notable correlations. "Average number of enrollments per lower division course" is strongly correlated with the "Total number of lower division courses taught" (r=0.856), indicating that faculty teaching a large number of LD courses are also typically teaching the higher enrollment LD courses. The "Average number of enrollments per UD course" shows a strong positive correlation with the "Total number of UD courses taught" (r=0.798), suggesting that faculty teaching a higher number of UD course sections also typically teaching the higher enrollment UD course sections. Additionally, the "Average number of undergraduate IR enrollments per term" is highly correlated with the "Total number terms on mentoring undergraduate IR course" (r=0.883), indicating that faculty who mentor more undergraduate students in IR also tend to mentor undergraduate students in IR across more terms. In terms of GR metrics, the "average number of enrollments per GR course" is strongly correlated with the "total number of GR courses taught" (r=0.850), suggesting that faculty who teach a greater number of GR course sections also have higher average enrollments per GR course section. Overall, the matrix highlights the connection between enrollment metrics and the number of course sections taught for a particular type of course (i.e. LD, UD, IR, GR) but also reveals the lack of a relationship between these metrics across course types (e.g., a lack of correlation between LD and UD course metrics). This highlights the variability of teaching productivity by the faculty and that there is no one-size-fits-all approach to teaching assignments and responsibilities.

[Table 4]

The last correlation matrix (Table 5) depicts the relationships between the eight teaching productivity metrics and eight research productivity metrics. The analysis indicates generally low to moderate correlations between the teaching and research metrics. Notably, “average number of undergraduate IR enrollments per term” shows weak positive correlations with several research metrics, including “Average citation count” (r=0.192), “Average citation per publication” (r=0.225), “Average h-index” (r=0.194), and “Average top 10% citation percentile” (r=0.221), suggesting that greater contributions to undergraduate IR experiences are weakly associated with increased research productivity. Similarly, “Average number of enrollments per GR course” is weakly correlated with “Average h-index” (r=0.216), and “Average scholarly outcome” (r=0.285), and moderately correlated with “Sum of grant awards” (r=0.420), indicating that higher average enrollments in graduate course sections are linked to faculty with a greater sum of grant awards. The strongest, yet still moderate, correlation observed is between “Total number of GR courses taught” and “Sum of grant awards” (r=0.455), suggesting that faculty who teach the most GR course sections also typically have received the largest amounts of grant funding. In contrast, the “Total number of LD courses taught” exhibits weak negative correlations with most research productivity metrics, including "Average citation count” (r=-0.131) and "Average h-index” (r=-0.122), implying that faculty with lower amounts of research productivity also teach the highest number of LD course sections. Overall, the matrix highlights that while there are some positive associations between teaching and research productivity metrics, these relationships are generally weak, with external funding demonstrating the strongest, yet modest, correlation between mentoring undergraduate IR and teaching GR courses.

[Table 5]

RQ 2: To what extent do faculty vary in terms of their research and teaching productivity metrics?

The cluster analysis revealed three distinct profiles based on the eight research and eight teaching productivity metrics. Research productivity metrics showed distinct levels across clusters while teaching productivity varied by course level. Cluster 1 (C1) exhibits high research productivity. Teaching productivity is low in LD courses, moderate in UD and GR courses, and high in IR mentorship. Cluster 2 (C2) shows moderate research productivity. Teaching productivity is high in LD and GR courses, moderate in UD courses, and low in IR mentorship. Cluster 3 (C3) demonstrates low research productivity. Teaching productivity is high in LD courses and low in UD, GR courses, and IR mentorship. The summary statistics for research and teaching productivity metrics by cluster are provided in the supplemental materials as Appendix C.

Table 6 presents the differences across the three clusters with respect to the research and teaching metrics. Each of the research productivity metrics showed significant differences across the clusters ($p<0.05$), suggesting substantial differences in research performance across the clusters. Similarly, we observed significant differences across the clusters of all teaching productivity metrics ($p<0.05$). Observing differences – for nearly all of the metrics – highlights the distinctness of both teaching and research productivity across the clusters.

[Table 6]

The median values for each research and teaching productivity metric within each cluster are visualized using a heatmap (Figure 1), providing a color-coded representation of the magnitude of each metric across the clusters. Additionally, Table 7 describes the characteristics of each cluster as summarized from the heatmap.

[Figure 1]

[Table 7]

RQ3: How do faculty characteristics (faculty type, rank, discipline, and demographic) correlate with the observed teaching and research productivity relationship?

Cluster Overview by overlaying the Faculty Demographics

Faculty characteristics (faculty type, rank, discipline, gender, the number of terms taught) were compared for the three resultant clusters. The comparisons of faculty type (RF, TF, lecturers), faculty rank (non-continuing lecturer, continuing lecturer, assistant professor, associate professor, full professor), gender (male, female), discipline (Physical sciences, Engineering, Biological sciences, Information and Computer Sciences), and the number of terms taught at the institution during the study period across the three clusters are detailed in Tables 8-10.

C1 has 217 faculty who are mostly male (Males=169, 78.9%; Females=48, 22.1%). The high research productivity cluster is dominated by RF (*n*=216, 99.5%), representing 44.4% of all RF in the study. In terms of discipline, there was a significant presence from the School of Biological Sciences (*n*=77), followed by the School of Engineering (*n*=52), the School of Physical Sciences (*n*=51), and the School of Information and Computer Sciences (*n*=36). This cluster contained mostly Full (*n*=118), followed by Assistant (*n*=63) and Associate Professors (*n*=35). There was only one TF in this cluster who was an assistant professor at the School of Biological Sciences, and lecturers were absent. Regarding teaching workload, faculty in C1 averaged 9.6 terms taught across all levels. This included 1.9 terms in teaching LD courses, 4.8 in UD courses, 4.7 in GR courses, and 9.2 in undergraduate IR courses on average during the study period.

C2 is the largest cluster (n=234) and was also predominately male (Males=177, 75.6%; Females=57, 24.4%). This cluster also predominantly consisted of RF (n=210, 89.7%), representing 43.2% of all RF in the study. Regarding discipline, there was a significant presence from the School of Physical Sciences (n=96), followed by School of Engineering (n=58), School of Information and Computer Sciences (n=29), and School of Biological Sciences (n=27). This cluster contained mostly Full RF (n=144), followed by Assistant Professors (n=34), and Associate Professors (n=32). There were only a handful of Lectures (n=8), predominantly non-continuing (n=6), mostly affiliated with School of Information and Computer Sciences (n=5). There were also several tenure-track TF (n=16, 6.8%) representing nearly half (47.1%) of all TF in the study, with the majority being Assistant Professors (n=11), primarily in School of Biological Sciences (n=9) and School of Physical Sciences (n=6). Regarding teaching workload, faculty in C2 had the highest average number of terms taught across all levels among the three clusters (12.7 terms). This included teaching 4.8 terms in LD courses, 5.2 in UD courses, 5.2 in GR courses, and 3.8 in undergraduate IR courses on average during the study period.

C3 is the smallest cluster, comprised of 102 faculty who were mostly male (Males=74, 72.5%; Females=28, 27.5%). Compared to the other clusters, there were fewer RF (*n*=60, 58.8%), representing 12.3% of all RF in the study. In terms of discipline, there was a significant presence from the School of Physical Sciences (*n*=21), followed by School of Information and Computer Sciences (*n*=16), School of Engineering (*n*=14), and the School of Biological Sciences (*n*=9). C3 contained mostly Full Professors (*n*=32), followed by Assistant Professors (n = 24), and Associate professors (*n*=21). This cluster included the largest number of lecturers (*n*=25, 24.5%), representing 75.8% of all lecturers in the study, with a notable presence in the School of Physical Sciences (*n*=16) and the School of Information and Computer Sciences (*n*=7). There were also several tenure-track-TF (n=17, 16.7%) representing half of all TF in the study. Regarding teaching workload, faculty in C3 have the second-highest average number of terms taught across all levels among the three clusters, 10.7 terms. This includes teaching 5.7 terms in LD courses, 4.1 in UD courses, 2.7 in GR courses, and 1.4 in undergraduate IR courses on average during the study period.

[Table 8]

[Table 9]

[Table 10]

There was no significant difference in the gender distribution across the clusters (*p*=0.58, Table 8). Moreover, there was no difference in the distribution of faculty rank among the lecturers across the clusters (*p*=0.69). Similarly, there was no difference in the distribution of faculty rank among the tenure-track-TF across the clusters (*p*=0.48). However, the results for lecturers and TF ranks may be attributed to relatively small sample sizes, potentially limiting the statistical power to detect confounding differences. In contrast, there was a difference in the distribution of faculty rank among the RF across the clusters ($p<0.001$). Additionally, there were significant differences across the clusters in the average number of terms that faculty taught at the LD, UD, GR, and in mentoring IR courses ($p<0.001$, Table 10).

The logistic regression analysis modeling the odds of being in C1 based on faculty characteristics is presented in Table 11. There was an increase in the odds of being in the high research productivity cluster for faculty who are on the tenure track but have not-yet-tenured (OR=2.01, $p=0.01$). Faculty from the Biological Sciences are more likely to be in C1 compared to each of the other disciplines (School of Engineering: OR=0.26, $p<0.001$; School of Information and Computer Sciences: OR=0.29, $p<0.001$; School of Physical Sciences OR=0.17, $p<0.001$). There was not a significant difference in the odds of being in C1 for male faculty compared to female faculty once we controlled for faculty rank and faculty type (OR=1.46, $p=0.16$).

[Table 11]

The second logistic regression analysis modeling the odds of the faculty being in C2 is provided in Table 12. Female, tenured, Biological Sciences, RF are less likely to be in C2 compared to the other faculty (OR=0.50, $p=0.02$). Faculty type shows varied impacts: lecturers have a non-significant decrease in log-odds by 0.84, while TF exhibited a non-significant increase by 0.21, highlighting a trend that TF were more likely to be in C2 than lecturers. Although the coefficients were not statistically significant ($p>0.05$), their signs and magnitudes provide meaningful insights into the relative likelihoods. Additionally, non-tenured faculty had a minimal and non-significant effect ($p=0.98$), whereas tenure-track faculty who were not-yet-tenured showed a significant decrease in log-odds by 0.57 ($p=0.02$). Faculty from the School of Engineering and School of Physical Sciences were more likely to be in C2 than faculty from the School of Biological Sciences (School of Engineering OR=2.05, $p=0.02$; School of Physical Sciences: OR=3.29, $p<0.001$). There was no difference in the odds of being in C2 for males compared to females after accounting for faculty type and faculty rank (OR=0.83, $p=0.45$).

[Table 12]

The logistic regression analysis modeling the odds of the faculty being in C3 is provided in Table 13. The baseline reference group (RG) across each of the variables ("RF" for faculty type, "Tenured" for tenure-status, "School of Biological Sciences" for discipline, and "Female" for gender) were significantly less likely to be in C3 compared to the other faculty (OR=0.07, p<0.001). There was a significant increase in the odds of lecturers (OR=14.44, p<0.001) and TF (OR=9.30, p<0.001) being in C3 compared to RF. Faculty tenure-status reveals that the non-tenured track had a non-significant decrease in log odds by 0.24 (p=0.82), and the not-yet-tenured track had a non-significant effect with a coefficient of 0.01 (p=0.98). There was a significant increase in the odds of being in C3 for faculty in the School of Information and Computer Sciences compared to faculty in the School of Biological Sciences (OR=2.72, p=0.03). There was no significant increase in the odds of being in C3 for males compared to females after adjusting for faculty type, faculty tenure-status, and discipline (OR=1.28, p=0.48).

[Table 13]

DISCUSSION

This study adds to the discussion surrounding research and teaching productivity in higher education by leveraging a unique combination of productivity metrics and STEM faculty demographic characteristics. These findings can help us better understand faculty roles, which is necessary for university administrators to support faculty success. Understanding these dynamics within the contexts of STEM fields is particularly crucial, as these disciplines are at the forefront of technological and scientific advancement, driving innovation and economic growth (Gibbs et al., 2014).

Overall, while many individual teaching and research metrics were tightly correlated with other metrics within that domain, there was little correlation between metrics across domains (Table 5). This highlights that while universities strive to support both teaching and research excellence, these goals may not be aligned within each faculty. One exception to this was a connection between research productivity metrics, including “Average citation per publication” and “Sum of grant awards” and the number of undergraduate IR mentored. This highlights that research-productive faculty may contribute to the university's teaching mission in ways other than classroom instruction, which is typically considered the hallmark of higher education instruction. In the context of STEM student success, there has been considerable research stressing the importance of the undergraduate research experience, as participation has been correlated with increased student retention, graduation rates, continuation to graduate school, and a sense of belonging in the discipline (Morales et al., 2017; Bozeman & Corley, 2004; Lee & Bozeman, 2005; Wuchty et al., 2007; Davis & Warfield, 2011; Laurance et al., 2013; Sax et al., 2002). This is particularly true for students from traditionally minoritized backgrounds (Eagan et al., 2013). So, while the C1 is characterized by high research productivity but low in LD courses, moderate in UD and GR courses, and high in IR courses for teaching productivity (Figure 1, Table 7), faculty within this cluster are contributing to the university's teaching mission by focusing on mentoring students in undergraduate IR experiences. As high research-productive faculty may appear to be more focused on the research relative to teaching, it is important that they receive appropriate support to develop their mentorship skills to maximize the benefits of these activities for their mentees.

By clustering the eight teaching and research productivity metrics, we identified three distinct clusters of faculty. Research productivity metrics showed distinct levels across clusters as high-moderate-low, but the teaching productivity showed more complex nuances across clusters. While faculty in C1 showed a high level of research productivity, their teaching productivity levels were low in LD courses, moderate in UD and GR courses, and high in IR courses relative to faculty in the other two clusters. While faculty in C2 and C3 show higher levels of teaching productivity in LD courses than C1, they presented lower teaching productivity in UD, GR, and IR courses than C1. This complexity may help to explain why prior work has produced conflicting results, ranging from a lack of a relationship between teaching and research productivity to both synergistic and antagonistic relationships between the two domains (Cadez et al., 2017; Galbraith & Merrill, 2012; Schapper & Mayson, 2010; Becker & Kennedy, 2005; Jonker & Hicks, 2014; Waltman et al., 2012; Fairweather, 2002; Winslow, 2010; Xu & Solanski, 2020; Keller et al., 2017; Figlio & Schapiro, 2017; Marsh & Hattie, 2002). It also emphasizes the need to include a range of metrics if we hope to gain a complete understanding of the relationship between teaching and research.

Including faculty demographic data in our analysis provided additional context to our findings. While prior work has produced conflicting results regarding the impact of gender on faculty productivity (Astin & Davis, 2019; Santo et al., 2009; Xu, 2008; Maphalala & Mpofu, 2017; Maske et al., 2003), gender in our sample was not predictive of which cluster a faculty might be affiliated with. Regarding discipline, Biological Sciences faculty were more likely to be found in the high research productivity cluster. This may reflect the greater availability of external funding to conduct biology-related research relative to that in other STEM fields. It may also reflect publication norms that more heavily weigh Biological Sciences journals or publications (National Science Foundation, 2020; U.S. Government Accountability Office, 2022). Similarly, it may reflect disciplinary norms related to teaching. It is documented that Biological Sciences faculty at this institution have lower teaching responsibilities than their colleagues in other STEM fields. It is also possible that either the discipline in general or the faculty specifically at this campus may place a greater emphasis on undergraduate IR mentorship. As prior work has highlighted the connection between undergraduate research experiences and faculty research productivity (Morales et al., 2017), it may be beneficial for programs to encourage their faculty to engage with students as part of the teaching mission, perhaps in exchange for other teaching responsibilities. While there is no demonstrable causal relationship between undergraduate IR mentorship and research productivity, prior work highlights that, at minimum (Brennan et al., 2019; Healey, 2005; Healey & Jenkins, 2005; Deem & Lucas, 2006), this can help to boost STEM undergraduate outcomes and help to create more inclusive academic programs.

Regarding faculty rank, our data surprisingly found that RF who were not-yet-tenured were also more likely to be found in C1. One would assume that more established faculty would exhibit higher research productivity metrics as the longer history of their research programs could positively impact their citation metrics and provide more opportunities to secure external funding. However, it is possible that more recently hired RF are conducting more cutting-edge research in their graduate and postdoctoral careers that are more connected to current research trends. Also, many funding opportunities are specifically geared toward new faculty to help get their work off the ground. This may also be influenced by lighter teaching loads that are often afforded to more recently hired faculty so that they can establish their research programs (Prince & Cotton, 2006). Regardless, it may be another signal of the growing need for institutions and funding agencies to support mid-career and later-career faculty research (Baker & Manning, 2021).

In terms of faculty position type, our data also enabled us to tease apart a small but noticeable difference between adjunct lecturers and TF in our data set. Regarding expectations, lecturers are meant to spend their time exclusively on classroom instruction, while TF at the study institution are meant to focus primarily on classroom instruction but also contribute to scholarly work and service activities (Harlow et al., 2020). Not surprisingly, both groups were overrepresented in C3, but while 25% of the lecturer population was found in C2, 50% of the TF were found in this cluster, and one of the TF was in C1. This is empirical evidence that these two faculty positions are having differential impacts. RF also have significant representation in Cluster 2, highlighting the substantial overlap in productivity between research and TF. This is surprising, considering the considerable resources afforded to RF relative to TF, including start-up package and lab space (Harlow et al., 2022). As research-intensive institutions strive to support research and teaching missions in the face of greater student enrollments and dwindling financial resources, TF may be an increasingly intriguing option relative to RF and lecturers.

While this study is more comprehensive than many in this area, the metrics used to evaluate teaching and research productivity—eight for each—do not fully capture all aspects of faculty work. These metrics primarily focus on lecture courses at both undergraduate and graduate levels, neglecting laboratory and seminar courses that often entail more varied and substantial workload responsibilities. By concentrating exclusively on lecture formats and overlooking important dimensions such as administrative duties and informal educational contributions, the study potentially misses critical elements of teaching and research productivity. This exclusion might limit the study's ability to comprehensively understand the true breadth of faculty responsibilities and their impact on perceived productivity.

Moreover, many of the research metrics employed have impacts that go beyond the defined study period of 2011 to 2017. For instance, citation metrics can reflect the influence of publications released before 2011, and the effects of significant publications towards the end of the study period may not be fully realized within the citation counts yet. Additionally, external funding figures captured might relate to grants awarded based on applications written prior to 2011, complicating the temporal alignment of data and skewing interpretations of productivity within the specific study period.

The data collected represent a single, research-intensive university and, as such, may have limited generalizability across other institutional contexts. While the STEM disciplines represented in the sample are common across higher education, the TF position type is unique. While these roles, which prioritize classroom instruction but also have scholarly and/or service expectations, are becoming more prominent (Harlow et al., 2020; Bush et al., 2011), this position is more unique in that these individuals are eligible for tenure (Harlow et al., 2020). As such, the presence of this position may influence the productivity of the traditional RF and lecturers in ways that may not be observed in other educational contexts.

CONCLUSION

This study underlines the nuanced relationship between research and teaching productivity within research-intensive environments, specifically within STEM programs. Through detailed analysis employing cluster and logistic regression models, the study illuminates the diversity in faculty roles and highlights how these roles correlate with productivity metrics across different demographics. The findings suggest that while research and teaching activities are traditionally viewed as separate endeavors, there is a complex interplay where engagements in one can influence achievements in the other. Particularly, the study reveals that faculty involvement in teaching, especially in mentoring undergraduate IR, often complements their research productivity, aligning with the dual mission of research-intensive universities to foster educational and research excellence.

Moving forward, it is essential for university administrators and policymakers to consider these insights when designing policies and support systems that enhance faculty productivity. Emphasizing the development of integrated roles that efficiently balance both research and teaching could lead to more robust academic contributions and fulfilling faculty experience, both of which have the potential to impact student success. Additionally, the differentiated impacts observed across various faculty demographics call for tailored approaches that recognize and nurture the unique contributions of diverse faculty groups, thereby promoting an inclusive academic environment that thrives on educational and research innovations.

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Table 1. Faculty Demographic Overview by Faculty Type, Rank, and Discipline

Faculty Type/Rank	Faculty Tenure-Status	School of Physical Sciences	School of Engineering	School of Biological Sciences	School of Information and Computer Sciences
Lecturers					
Non-Continuing	Non-tenured	13	2	0	7
Continuing	Tenured	5	1	0	5
Total		18	3	0	12
Teaching Faculty (TF)					
Assistant	Not-yet-tenured	8	2	8	1
Associate	Tenured	3	1	3	3
Full	Tenured	1		3	1
Total		12	3	14	5
Research Faculty (RF)					
Assistant	Not-yet-tenured	35	31	32	16
Associate	Tenured	25	23	16	17
Full	Tenured	108	70	65	48
Total		168	124	113	81
Grand Total		198	130	127	98

Table 2. Faculty Demographic Overview by Gender and Discipline

Gender	School of Physical Sciences	School of Engineering	School of Biological Sciences	School of Information and Computer Sciences
Male	151	107	90	72
Female	47	23	37	26
Total	198	130	127	98

Table 3. Correlation of Research Productivity (RP) Attributes

Research Productivity Metrics	RP1	RP2	RP3	RP4	RP5	RP6	RP7	RP8
(RP1) Average citation count	-							
(RP2) Average citation per publication	0.948	-						
(RP3) Average field-weighted citation impact	0.890	0.912	-					
(RP4) Average h-index	0.899	0.825	0.749	-				
(RP5) Average top 10% citation percentile	0.849	0.868	0.788	0.712	-			
(RP6) Average publication top 10 citescore	0.830	0.839	0.717	0.797	0.756	-		
(RP7) Average scholarly outcome	0.888	0.710	0.702	0.855	0.682	0.683	-	
(RP8) Sum of grant awards ($)	0.457	0.399	0.360	0.442	0.421	0.413	0.477	-

Table 4. Correlation of Teaching Productivity Attributes

Teaching Productivity Metrics	TP1	TP2	TP3	TP4	TP5	TP6	TP7	TP8
(TP1) Average enrollment LD	-							
(TP2) Average enrollment UD	-0.206	-						
(TP3) Average enrollment IR	-0.153	0.193	-					
(TP4) Average enrollment GR	-0.154	0.149	-0.078	-				
(TP5) Total LD courses	0.856	-0.210	-0.175	-0.239	-			
(TP6) Total UD courses	-0.142	0.798	0.204	0.125	-0.102	-		
(TP7) Total IR terms	-0.123	0.185	0.883	-0.081	-0.153	0.208	-	
(TP8) Total GR courses	-0.121	0.150	-0.082	0.850	-0.198	0.137	-0.072	-

Table 5. Correlation of Teaching and Research Productivity Attributes

	RP1	RP2	RP3	RP4	RP5	RP6	RP7	RP8
TP1	-0.031	0.001	-0.038	-0.034	-0.004	0.006	-0.082	-0.081
TP2	0.032	0.030	0.037	0.052	0.030	0.081	0.040	0.188
TP3	0.192	0.225	0.115	0.194	0.221	0.204	0.120	0.212
TP4	0.208	0.126	0.160	0.216	0.080	0.171	0.285	0.420
TP5	-0.131	-0.100	-0.119	-0.122	-0.109	-0.112	-0.168	-0.203
TP6	0.014	0.017	0.010	0.061	0.003	0.073	0.016	0.155
TP7	0.214	0.271	0.139	0.212	0.244	0.235	0.108	0.236
TP8	0.227	0.140	0.176	0.256	0.102	0.202	0.316	0.455

Table 6. Differences in research and teaching productivity metrics across three clusters using ANOVA and Kruskal-Wallas tests.

	ANOVA		Kruskal-Wallas
	F-value	*p*	*p*
(RP1) Average citation count	946.3	< 0.001	< 0.001
(RP2) Average citation per publication (RP2)	756.1	< 0.001	< 0.001
(RP3) Average field weighted citation impact	694.9	< 0.001	< 0.001
(RP4) Average h-index	669.8	< 0.001	< 0.001
(RP5) Average top 10% citation percentile	346.9	< 0.001	< 0.001
(RP6) Average publication top 10 citescore	334.6	< 0.001	< 0.001
(RP7) Average scholarly outcome	327.8	< 0.001	< 0.001
(RP8) Sum of grant awards	71.3	< 0.001	< 0.001
(TP1) Average Enrollment LD	54.4	< 0.001	< 0.001
(TP2) Average Enrollment UD	5.1	0.01	0.03
(TP3) Average Enrollment IR	39.5	< 0.001	< 0.001
(TP4) Average Enrollment GR	19.3	< 0.001	< 0.001
(TP5) Total LD Courses	50.1	< 0.001	< 0.001
(TP6) Total UD Courses	6.6	< 0.001	0.01
(TP7) Total IR Terms	48.9	< 0.001	< 0.001
(TP8) Total GR Courses	22.6	< 0.001	< 0.001

Table 7. Cluster Characteristics and Description Summary

Cluster	Description

C1	• C1 exhibits generally higher median (med) values across all research metrics relative to C2 and C3.
	  ○ This cluster peaks notably in “average top 10% citation percentile” (med=0.77), “average publication top 10 citescore” (med=0.63), and “sum of grant awards” (med=0.59), indicating a strong presence in top-tier publications.
	• The results of the teaching productivity metrics are more variable than those of research productivity metrics.
	  ○ Negative values are observed for the metrics related to lower-division (LD) courses (“average number of enrollments per LD course,” med=-1.24; “total number of LD courses taught,” med=-1.10). This implies low teaching productivity in LD courses.
	  ○ Moderate values are observed for the metrics related to upper-division (UD) courses (“average number of enrollments per UD course,” med = 0.34; “total number of UD courses taught,” med= 0.32) and graduate-level (GR) courses (“average number of enrollments per GR course,” med=0.35; “total number of GR courses taught,” med=0.27). This implies moderate levels of teaching productivity in UD and GR courses.
	  ○ High values are observed for the metrics related to undergraduate independent research (IR) mentoring courses (“average number of enrollments per IR course,” med=0.46; “total number of terms of mentoring IR courses,” med=0.74). This implies high teaching productivity in IR courses.

C2	• C2 exhibits generally moderate median (med) values across all research metrics relative to C1 and C3.
	• The results of the teaching productivity metrics are more variable than those of research productivity metrics.
	  ○ Negative values are observed for the metrics related to undergraduate independent research (IR) mentoring courses (“average number of enrollments per IR course,” med=-0.81; “total number of terms of mentoring IR courses,” med=-0.81). This implies low teaching productivity in IR courses.
	  ○ Moderate values are observed for the metrics related to upper-division (UD) courses (“average number of enrollments per UD course,” med = 0.30; “total number of UD courses taught,” med= 0.32). This implies moderate levels of teaching productivity in UD courses.
	  ○ High values are observed for the metrics related to lower-division (LD) courses (“average number of enrollments per LD course,” med=0.67; “total number of LD courses taught,” med=0.45) and graduate-level (GR) courses (“average number of enrollments per GR course,” med=0.45; “total number of GR courses taught,” med=0.44). This implies high teaching productivity in LD and GR courses.

C3	• C3 exhibits generally low median (med) values, which are all negative, across all research metrics relative to C1 and C2.
	• The results of the teaching productivity metrics are more variable than those of research productivity metrics.
	  ○ Negative values are observed for the metrics related to undergraduate independent research (IR) mentoring courses ("average number of enrollments per IR course," med=-0.81; "total number of terms of mentoring IR courses," med=-0.81). This implies low teaching productivity in IR courses.
	  ○ Also, significantly low values were observed for the metrics related to upper-division (UD) courses ("average number of enrollments per UD course," med = 0.07; "total number of UD courses taught," med=-0.20) and graduate-level (GR) courses ("average number of enrollments per GR course," med=0.07; "total number of GR courses taught," med=-0.63). This implies low levels of teaching productivity in UD and GR courses.
	  ○ High values are observed for the metrics related to lower-division (LD) courses ("average number of enrollments per LD course," med=0.67; "total number of LD courses taught," med=0.45). This implies high teaching productivity in LD courses.

Table 8. Gender distribution, Faculty Type, and Rank Comparison by clusters

	Cluster 1	**Cluster 2**	**Cluster 3**	***p***
Gender				0.58
Female	48	57	28	
Male	169	177	74	
Faculty Type/Rank				
Lecturers	0	8	25	0.69[a]
Non-continuing	0	6	16	
Continuing	0	2	9	
Teaching Faculty (TF)	1	16	17	0.48[a]
Assistant	1	11	7	
Associate	0	3	7	
Full	0	2	3	
Research Faculty (RF)	216	210	60	< 0.001
Assistant	63	34	17	
Associate	35	32	14	
Full	118	144	29	
Total	217	234	102	

Note: Chi-square test used unless otherwise noted. a Fisher's exact test used.

Table 9. Discipline Comparison by Clusters

Cluster	Faculty Type/Rank	School of Physical Sciences	School of Engineering	School of Biological Science	School of Information and Computer Sciences
1	Teaching Faculty (TF)	0	0	1	0
	Assistant	0	0	1	0
	Research Faculty (RF)	51	52	77	36
	Assistant	15	13	27	8
	Associate	7	11	8	9
	Full	29	28	42	19
	Total	51	52	78	36
2	Lecturers	2	1	0	5
	Non-continuing	2	1	0	3
	Continuing	0	0	0	2
	Teaching Faculty (TF)	6	0	9	1
	Assistant	5	0	5	1
	Associate	1	0	2	0
	Full	0	0	2	0
	Research Faculty (RF)	96	58	27	29
	Assistant	15	12	3	4
	Associate	15	9	4	4
	Full	66	37	20	21
	Total	104	59	36	35
3	Lecturers	16	2	0	7
	Non-continuing	11	1	0	4
	Continuing	5	1	0	3
	Teaching Faculty (TF)	6	3	4	4
	Assistant	3	2	2	0
	Associate	2	1	1	3
	Full	1	0	1	1
	Research Faculty (RF)	21	14	9	16
	Assistant	5	6	2	4
	Associate	3	3	4	4
	Full	13	5	3	8
	Total	43	19	13	27
Grand Total		198	130	127	98

Table 10. Comparison of the Average Number of Terms that faculties taught by clusters

	Cluster 1	**Cluster 2**	**Cluster 3**	***F***	***p***
Average # of Terms Taught	9.6	12.7	10.7	15.41	< 0.001
Lower Division	1.9	4.8	5.7	27.53	< 0.001
Upper Division	4.8	5.2	4.1	12.11	< 0.001
Graduate Level	4.7	5.2	2.7	13.16	< 0.001
Independent Research Mentoring	9.2	3.8	1.4	39.59	< 0.001

Table 11. Logistic Regression Coefficient Statistic Summary for Cluster 1

	β	**OR**	**SE**	**95% CI [LL, UL]**	**z**	**P>|z|**
Intercept	0.47	1.60	0.32	[-0.16, 1.09]	1.47	0.14
Faculty Tenure-Status						
RG: Tenured						
Not-yet-tenured status	0.70	2.01	0.26	[0.19, 1.22]	2.67	0.01
Discipline						
RG: School of Biological Sciences						
School of Engineering	-1.35	0.26	0.32	[-1.97, -0.73]	-4.27	< 0.001
School of Information and Computer Science	-1.24	0.29	0.34	[-1.91, -0.56]	-3.6	< 0.001
School of Physical Sciences	-1.79	0.17	0.3	[-2.38, -1.19]	-5.89	< 0.001
Gender						
RG: Female						
Male	0.38	1.46	0.27	[-0.15, 0.91]	1.4	0.16

** Logistic regression for Cluster 1 is conducted exclusively considering Research Faculty (RF).*

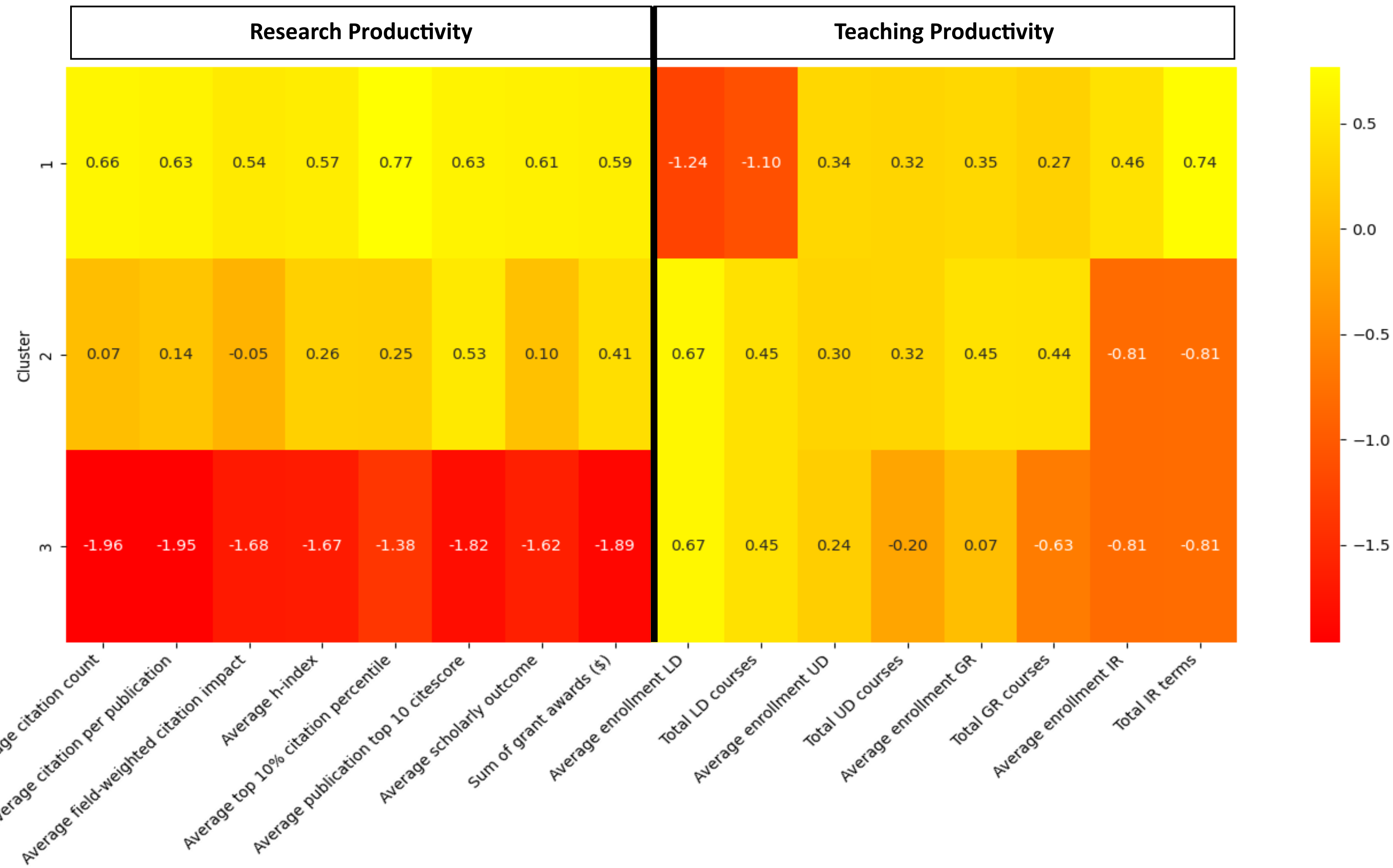
Table 12. Logistic Regression Coefficient Statistic Summary for Cluster 2

	β	**OR**	**SE**	**95% CI [LL, UL]**	**z**	**P>|z|**
Intercept	-0.70	0.50	0.3	[-1.29, -0.10]	-2.30	0.02
Faculty Type						
RG: Research Faculty (RF)						
Lecturers	-0.84	0.43	0.87	[-2.54, 0.86]	-0.97	0.33
Teaching Faculty	0.21	1.23	0.44	[-0.65, 1.08]	0.49	0.63
Faculty Tenure-Status						
RG: Tenured						
Non-tenured	0.03	1.03	1.02	[-1.98, 2.03]	0.03	0.98
Not-yet-tenured	-0.57	0.57	0.25	[-1.06, -0.08]	-2.28	0.02
Discipline						
RG: School of Biological Sciences						
School of Engineering	0.72	2.05	0.31	[0.12, 1.32]	2.34	0.02
School of Information and Computer Science	0.44	1.55	0.33	[-0.20, 1.07]	1.34	0.18
School of Physical Sciences	1.19	3.29	0.28	[0.65, 1.74]	4.3	< 0.001
Gender						
RG: Female						
Male	-0.19	0.83	0.25	[-0.67, 0.30]	-0.75	0.45

Table 13. Logistic Regression Coefficient Statistic Summary for Cluster 3

	β	OR	SE	95% CI [LL, UL]	z	P>|z|
Intercept	-2.68	0.07	0.47	[-3.60, -1.76]	-5.69	< 0.001
Faculty Type						
RG: Research Faculty (RF)						
Lecturers	2.67	14.44	0.87	[0.96, 4.38]	3.06	< 0.001
Teaching Faculty	2.23	9.30	0.46	[1.32, 3.14]	4.81	< 0.001
Faculty Tenure-Status						
RG: Tenured						
Non-tenured	-0.24	0.79	1.02	[-2.23, 1.76]	-0.23	0.82
Not-yet-tenured	0.01	1.01	0.34	[-0.66, 0.68]	0.03	0.98
Discipline						
RG: School of Biological Sciences						
School of Engineering	0.31	1.36	0.48	[-0.63, 1.24]	0.64	0.52
School of Information and Computer Science	1.00	2.72	0.45	[0.12, 1.87]	2.23	0.03
School of Physical Sciences	0.66	1.93	0.41	[-0.14, 1.46]	1.62	0.11
Gender						
RG: Female						
Male	0.25	1.28	0.35	[-0.44, 0.93]	0.71	0.48

Figure 1. Summary of Ratings of Teaching and Research Productivity



Appendix A.

Definition of Research Productivity (RP) and Teaching Productivity (TP) Metrics.

Productivity Metrics	Abbreviation	Definition	Data Source
Research			
Average citation count	RP1	Average number of citations during the study period	SciVal
Average citation per publication	RP2	Average number of citations per publication during the study period	SciVal
Average field-weighted citation impact	RP3	The average ratio of citations received relative to the expected world average for the subject field, publication type and publication year, averaged over the study period	SciVal
Average h-index	RP4	A measure of both the productivity and citation impact of an entity, based on the number of publications as well as the number of citations they have received, averaged over the study period	SciVal
Average top 10% citation percentile	RP5	Average number of publications of a researcher that are highly cited, having reached a threshold (top 10%) of citations received	SciVal
Average publication top 10 citescore	RP6	Average number of publications of a selected entity that have been published in the world's top journals	SciVal
Average scholarly outcome	RP7	Average number of publications in the study period	SciVal
Sum of grant awards ($)	RP8	The total amount of grant dollars awarded during the study period	Institution
Teaching			
Average enrollment LD	TP1	Average number of enrollments per lower division course	Institution
Average enrollment UD	TP2	Average number of enrollments per upper division course	Institution
Average enrollment IR	TP3	Average number of independent research undergraduate enrollments per term	Institution
Average enrollment GR	TP4	Average number of enrollments per graduate course	Institution
Total LD courses	TP5	Total number of lower division courses taught	Institution
Total UD courses	TP6	Total number of upper division courses taught	Institution
Total IR terms	TP7	Total number of terms mentoring undergraduate students in independent research	Institution
Total GR courses	TP8	Total number of Graduate courses taught	Institution

Appendix B.

Descriptive Statistics of Faculty Teaching and Research Productivity Attributes

	Mean (SD)	**Median (Min-Max)**	**IQR (Q1-Q3)**
Research Productivity Metrics			
(RP1) Average citation count	271.8 (743.4)	83.6 (0-8820)	228.9 (17.0-245.9)
(RP2) Average citation per publication	38.0 (85.6)	22.4 (0-1762.3)	37.5 (8.0-45.5)
(RP3) Average field-weighted citation impact	1.8 (3.5)	1.3 (0.0-75.0)	1.6 (0.6-2.2)
(RP4) Average h-index	27.2 (22.5)	24.0 (0.0-132.0)	27 (11.0-38.0)
(RP5) Average top 10% citation percentile	20.9 (22.0)	14.8 (0.0-140.3)	35.7 (0.0-35.7)
(RP6) Average publication top 10 citescore	43.0 (32.0)	47.1 (0.0-175.7)	58.6 (11.1-69.7)
(RP7) Average scholarly outcome	4.9 (8.9)	3.1 (0.0-124.3)	5.2 (0.9-6.1)
(RP8) Sum of grant awards ($)	2,065,708 (3,822,680)	799,999 (0-37,832,465)	2,655,670 (56,000-2,711,670)
Teaching Productivity Metrics			
(TP1) Average enrollment LD	95.3 (111.7)	62.0 (0.0-450.0)	149.0 (0.0-149.0)
(TP2) Average enrollment UD	49.1 (53.8)	33.0 (0.0-332.2)	58.3 (11.7-70)
(TP3) Average enrollment IR	1.3 (2.5)	0.0 (0.0-29.5)	1.8 (0.0-1.8)
(TP4) Average enrollment GR	12.4 (11.5)	10.7 (0.0-86.5)	13 (4.5-17.5)
(TP5) Total LD courses	5.8 (11.2)	2.0 (0.0-112.0)	7.0 (0.0-7.0)
(TP6) Total UD courses	6.2 (7.6)	4.0 (0.0-87.0)	8.0 (1.0-9.0)
(TP7) Total IR terms	6.0 (10.0)	0.0 (0.0-56.0)	9.0 (0.0-9.0)
(TP8) Total GR courses	5.2 (5.0)	4.0 (0.0-23.0)	7.0 (1.0-8.0)

Appendix C

Descriptive Statistics of Faculty Teaching and Research Productivity Attributes by Cluster

	Cluster 1		
	Mean (SD)	**Median (Min-Max)**	**IQR (Q1-Q3)**
Research Productivity Metrics			
(RP1) Average citation count	525.1 (1109.8)	231.4 (30-8820)	344.0 (107-451)
(RP2) Average citation per publication	64.4 (126.3)	42.1 (4.9-1762.3)	45.2 (27-72.2)
(RP3) Average field-weighted citation impact	2.7 (5.2)	2.0 (0.6-75)	1.4 (1.4-2.8)
(RP4) Average h-index	40.7 (22.7)	34.0 (1.0-132.0)	25.0 (26.0-51.0)
(RP5) Average top 10% citation percentile	34 (20.6)	29.8 (0.0-140.3)	30.0 (18.1-48.1)
(RP6) Average publication top 10 citescore	58.3 (24.4)	60.4 (0.0-175.7)	30.3 (45-75.3)
(RP7) Average scholarly outcome	8.1 (12.6)	5.4 (0.1-124.3)	5.5 (3.1-8.6)
(RP8) Sum of grant awards ($)	2,970,926 (4,346,566)	1,871,338 (0-33,357,468)	3,156,291 (623,722-3,780,013)
Teaching Productivity Metrics			
(TP1) Average enrollment LD	71.8 (118.4)	0.0 (0.0-450.0)	123.3 (0.0-123.3)
(TP2) Average enrollment UD	52.1 (55.6)	35.4 (0.0-289.0)	66.8 (10-76.8)
(TP3) Average enrollment IR	1.9 (2.7)	1.3 (0.0-28.0)	2.7 (0-2.7)
(TP4) Average enrollment GR	11.7 (10.6)	10.3 (0.0-65.0)	12.7 (4-16.7)
(TP5) Total LD courses	2.4 (4.5)	0.0 (0.0-28.0)	3.0 (0.0-3.0)
(TP6) Total UD courses	5.9 (5.6)	5.0 (0.0-29.0)	8.0 (1.0-9.0)
(TP7) Total IR terms	10.1 (11.6)	6.0 (0.0-44.0)	18.0 (0.0-18.0)
(TP8) Total GR courses	5.5 (5.4)	4.0 (0.0-21.0)	8.0 (1.0-9.0)

	Cluster 2		
	Mean (SD)	**Median (Min-Max)**	**IQR (Q1-Q3)**
Research Productivity Metrics			
(RP1) Average citation count	154.6 (249.0)	57.6 (0-1771.3)	128.1 (25.5-153.6)
(RP2) Average citation per publication	29.7 (35.4)	20.2 (0-362.9)	24.3 (10.2-34.5)
(RP3) Average field-weighted citation impact	1.6 (1.4)	1.1 (0.0-10.5)	1.1 (0.8-1.9)
(RP4) Average h-index	25.6 (16.5)	22.0 (1.0-92.0)	19.0 (14.0-33.0)
(RP5) Average top 10% citation percentile	17.8 (19.8)	10.7 (0.0-100.0)	29.7 (0.0-29.7)
(RP6) Average publication top 10 citescore	47.6 (28.7)	49.1 (0.0-100.0)	45.9 (24.8-70.7)
(RP7) Average scholarly outcome	4.1 (4.4)	2.9 (0.0-30.0)	4.2 (1.1-5.3)
(RP8) Sum of grant awards ($)	1,683,831 (3,003,146)	617,804 (0-31,855,821)	2,242,505 (55,250-2,297,755)
Teaching Productivity Metrics			
(TP1) Average enrollment LD	119.2 (107.8)	92.7 (0.0-445.0)	139.1 (38.7-177.8)
(TP2) Average enrollment UD	48.7 (51.3)	32.9 (0.0-332.2)	45.0 (15.4-60.4)
(TP3) Average enrollment IR	1.0 (2.6)	0.0 (0.0-29.5)	1.2 (0.0-1.2)
(TP4) Average enrollment GR	14.2 (11.1)	12.2 (0.0-58.0)	12.6 (7.4-20)
(TP5) Total LD courses	6.6 (8.0)	4.0 (0.0-49.0)	7.8 (1.0-8.8)
(TP6) Total UD courses	6.7 (7.6)	5.0 (0.0-64.0)	7.0 (2.0-9.0)
(TP7) Total IR terms	4.1 (8.8)	0.0 (0.0-56.0)	3.8 (0.0-3.8)
(TP8) Total GR courses	5.8 (4.6)	5.0 (0.0-23.0)	6.0 (2.0-8.0)

	Cluster 3		
	Mean (SD)	**Median (Min-Max)**	**IQR (Q1-Q3)**
Research Productivity Metrics			
(RP1) Average citation count	1.8 (4.5)	0.0 (0.0-27.0)	0.0 (0.0-0.0)
(RP2) Average citation per publication	1.0 (2.3)	0.0 (0.0-11.0)	0.0 (0.0-0.0)
(RP3) Average field-weighted citation impact	0.1 (0.3)	0.0 (0.0-1.1)	0.0 (0.0-0.0)
(RP4) Average h-index	2.2 (3.7)	1.0 (0.0-19.0)	2.8 (0.0-2.8)
(RP5) Average top 10% citation percentile	0.0 (0.0)	0.0 (0.0-0.0)	0.0 (0.0-0.0)
(RP6) Average publication top 10 citescore	0.0 (0.0)	0.0 (0.0-0.0)	0.0 (0.0-0.0)
(RP7) Average scholarly outcome	0.2 (0.6)	0.0 (0.0-3.7)	0.1 (0.0-0.1)
(RP8) Sum of grant awards ($)	1,015,973 (3,929,784)	0 (0-37,832,465)	689,691 (0-689,691)
Teaching Productivity Metrics			
(TP1) Average enrollment LD	90.4 (94.4)	92.2 (0.0-347.6)	127.6 (0.0-127.6)
(TP2) Average enrollment UD	43.8 (55.4)	29.3 (0.0-290.0)	59.6 (0.0-59.6)
(TP3) Average enrollment IR	0.4 (1.0)	0.0 (0.0-5.0)	0.0 (0.0-0.0)
(TP4) Average enrollment GR	9.7 (13.6)	6.6 (0-86.5)	14.6 (0.0-14.6)
(TP5) Total LD courses	11.4 (21)	4.0 (0.0-112.0)	11.5 (0.0-11.5)
(TP6) Total UD courses	5.9 (10.7)	2.5 (0.0-87.0)	6.8 (0.0-6.8)
(TP7) Total IR terms	1.4 (4.4)	0.0 (0.0-31.0)	0.0 (0.0-0.0)
(TP8) Total GR courses	3.0 (4.4)	1.0 (0.0-20.0)	4.0 (0.0-4.0)