The Relationship Between Responsibility Center Management, Faculty Composition, and Faculty Salaries

Chelsea H. Lyles

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David Knight, Chair

Andrew Katz

David Kniola

Claire K. Robbins

Ken Smith

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Abstract

In 2006–2007 ten public universities were utilizing responsibility center management (RCM), and that number increased to 24 in 2014–2015 (Jaquette, Kramer, & Curs, 2018), but little is known about the relationship between the implementation of RCM, faculty composition, and faculty compensation. Inequities in faculty composition and salaries exist based on gender and race/ethnicity. My study explored whether the implementation of RCM, an increasingly popular budget model in public higher education, was associated with further faculty salary and compositional inequities by gender and race/ethnicity. Deans, as heads of revenue centers under RCM, have increased budgetary power and decision-making responsibility. Organizational justice theory, specifically the tenets of distributive justice and procedural justice, grounded this study by connecting the implementation of RCM to the diffusion of decision-making throughout the organization and potential association with inequities in faculty composition and faculty compensation. This quantitative study examined the relationship of RCM with institutional average salary and numerical proportions of assistant professors on the tenure track at public, doctoral universities based on the 2015 Basic Carnegie Classification. I used difference-in-difference estimation to compare institutions that implemented RCM (treatment group) to institutions that did not (control group) to determine whether there were differences in salary and proportional trends for assistant professors by gender and by gender and race. In addition, I explored engineering in a specific set of analyses because it has been cited as a field that should especially benefit from an RCM budgeting approach. I compared the change in proportions of assistant professors of engineering by gender and by gender and race/ethnicity at universities within the sample. Finally, the annual salaries of a subset of assistant professors of engineering within the sample of doctoral institutions in the treatment and control groups in Ohio were compared. Across these different analyses, I did not find evidence that RCM implementation between FY2012 – FY2017 had a significant effect on average institutional salary generally or by gender or race/ethnicity for assistant professors broadly or within engineering, specifically. Lacking a comprehensive dataset with institutional and individual predictors of faculty compensation and composition, and as RCM models vary among institutions, these findings should be interpreted cautiously. As RCM did not appear to be associated with any changes in faculty composition or compensation practices, I did not find evidence that RCM implementation had a significant impact on the procedural justice (i.e., decision-making criteria and processes of deans or department heads) or distributive justice (i.e., salary amounts or proportions of who was hired by gender and race/ethnicity) of faculty composition or faculty compensation at public, doctoral universities.

The Relationship Between Responsibility Center Management, Faculty Composition, and Faculty Salaries

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General Audience Abstract

My study explored whether the implementation of responsibility center management, an increasingly popular budget model at public universities, was associated with differences in faculty salary and faculty numbers by gender and race/ethnicity. Deans, as heads of revenue centers under RCM, have increased budgetary power and decision-making responsibility. Organizational justice theory, specifically the tenets of distributive justice and procedural justice, grounded this study by connecting the implementation of RCM to the diffusion of decision-making throughout the organization and potential association with inequities in faculty composition and faculty compensation. I examined the relationship of RCM with institutional average salary and numerical proportions of assistant professors on the tenure track at public, doctoral universities. I compared institutions that implemented RCM to institutions that did not to determine whether there were differences in salary and proportions for assistant professors by gender and by gender and race/ethnicity. In addition, I explored engineering because it has been cited as a field that should especially benefit from an RCM budgeting approach. I compared the change in proportions of assistant professors of engineering by gender and by gender and race/ethnicity. Finally, the annual salaries of assistant professors of engineering at two universities in Ohio were compared. Across these different analyses, I did not find evidence that RCM implementation had a significant effect on salary or proportions of assistant professors; however, as my study had lots of limitations, and as RCM models vary among universities, these findings should be interpreted cautiously. As RCM did not appear to be associated with any changes, I inferred that RCM implementation did not have a significant impact on the procedural justice (i.e., decision-making criteria and processes of deans or department heads) or distributive justice (i.e., salary amounts or proportions of who was hired by gender and race/ethnicity) of faculty salary or proportions at public, doctoral universities.

Dedication

To my mother, Judith Beckford Haines, for a lifetime of love, encouragement, and raising the bar. You inspired me to finish what you started so many years ago.

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Chapter One

College affordability is a both a current and long-standing top higher education state policy issue (AASCU Government Relations and Policy Analysis Division, 2019). Rising tuition and fees and student debt have received significant attention in the popular press and among state and federal policymakers (Thompson, 2012; Washington, 2016). Many state governments have capped tuition and fees to stem rising college student debt while simultaneously reducing state appropriations for higher education. College students have rarely paid for the full amount it costs universities to provide the student an education; however, following the 2008 recession, federal and state support was diverted from higher education to manage increased federal budget and trade deficits (Goldstein, 2012). In 2003, state subsidies comprised approximately 56% of education and related costs at public research universities and tuition comprised the remaining 44%. By 2013, the percentage of state subsidies had dropped to 38% and the percentage of student tuition rose to 62% (Desrochers & Hurlburt, 2016). State appropriations for higher education were almost $2,000 less per student in 2017 than they were in 2001 and have not kept pace with rising enrollments (State Higher Education Executive Officers, 2018). And in 2019, for example, Alaska Governor Mike Dunleavy proposed cutting $135 million from the University of Alaska system for the 2020 fiscal year, a 41% cut in state funding for the University of Alaska. At one point, terminating tenured faculty members was part of the plan to eliminate an estimated 1,300 positions in the university system, which employed approximately 6,600 people (Hughes & Svrluga, 2019).

In response to this challenging financial environment, many universities have implemented incentive-based budgeting as a strategy to increase tuition revenue (Jaquette et al., 2018), track and allocate revenues and expenditures, and achieve institutional strategic priorities

(Kosten, 2016; Vonasek, 2011). Responsibility center management (RCM) is the most popular decentralized, incentive-based budget model. Other variants of incentive-based budgeting have included responsibility center budgeting, revenue-centered budgeting, value-centered management, and revenue responsibility budgeting (Vonasek, 2011; Zierdt, 2009). RCM is viewed as an alternative to incremental budgeting, the budget model traditionally used in public higher education. Under incremental budgeting, each unit had a “base” budget, and each year new funds were requested from central administration on top of that base layer. Unrestricted revenue, such as tuition, investment income, and unrestricted gifts were controlled centrally (Goldstein, 2012). Borrowing from the corporate sector, RCM was first implemented at Harvard in the 1970s before spreading widely to private institutions of higher education (Zierdt, 2009). The Harvard model was nicknamed “every tub on its bottom” (Goldstein, 2012, p. 98) because of its exceedingly decentralized nature where academic units maintained a high level of autonomy and decision-making power.

The number of public universities adopting RCM increased from 10 in 2006–2007 to 24 in 2014–2015 (Jaquette et al., 2018). Under RCM, central university administrators calculate revenues, such as tuition and philanthropy, and expenses and then allocated the revenues and expenses to decentralized units, such as academic colleges. Each unit pays a fee, or tax, back to the university’s central administration for shared expenses, such as facilities, admissions, and student affairs. Faculty compensation is an example of an instructional expense that would be allocated to the college level under a typical RCM model. There are several seemingly promising elements of RCM, but little empirical research has been conducted on the outcomes of RCM. The decentralization afforded by RCM grants increased decision-making and budgetary power to the college level, and especially to deans. Given its emphasis on decentralization, it stands to reason that diffused authority and varied decision-making processes and values could result in varied outcomes.

Deans in an RCM environment are closer in the organization to faculty. This proximity may create a new challenge for deans and faculty alike when it comes to faculty composition and compensation. Compensation schemes vary among institutions, faculty type, and disciplines. Faculty feel salaries are awarded using ambiguous and subjective means (Wallace & King, 2013), and faculty members are often frustrated by a lack of transparency in performance measures and compensation (Carson, 2013).

Like other industries, academia has benefited from and would benefit from more diversity. Diversity facilitates economic benefits, innovation, and creativity (AlShebli, Rahwan, & Woon, 2018). AlShelbli, Rahwan, and Woon (2018) found that diversity (a combination of age, gender, affiliation, and ethnicity) had a significant, positive impact on scientific collaborations as measured by research productivity, and ethnic diversity had the strongest correlation with research productivity. Unfortunately, unexplained salary gaps by gender and race/ethnicity have undermined faculty perceptions of fair pay. Faculty compensation at public, doctoral universities is higher for men than women (American Association of University Professors, 2018; Meyers, 2011). At public, selective universities, faculty who identified as Black or Latino earned a smaller annual salary than White faculty in 2015-2016 (D. Li & Koedel, 2017).

Faculty compensation has also varied by discipline (Stack, 2014), as have faculty and deans' perceptions of the impact of RCM implementation. As one way to control for effect of academic discipline on faculty composition and compensation and to better understand college-level outcomes of RCM implementation, I chose to conduct a deeper analysis of faculty composition and compensation by RCM implementation within a discipline. Because of its importance to economic development (Centre for Economics and Business Reseach, 2016), stakeholder interest in diversification (Cox et al., 2017; Okahana, Klein, Allum, & Sowell, 2018), and being assumed to fare well in RCM environments (Curry, Laws, & Strauss, 2013), I chose to extend and deepen my analysis of faculty composition and compensation at public universities through the engineering discipline.

Policies such as RCM impact groups differently, and often policymakers are unable to foresee the impacts and unintended consequences of policy implementation. For example, performance-based funding (PBF) is a state-wide policy that links state funding for higher education to outcomes identified by state policymakers, such as degree completion, earned credits or job placement rates of graduates, operational efficiency, and/or success for underrepresented student groups (Kelderman, 2019). States link PBF to funding allocations for higher education with the hope of incentivizing more efficient and effective higher education operations (Kelchen, 2018). Early PBF adoption was not found to have positive impacts on graduation rates (Rutherford & Rabovsky, 2014; Shin, 2010; Shin & Milton, 2004), degree completion (Hillman, Tandberg, & Gross, 2014), retention rates (Rutherford & Rabovsky, 2014; Sanford & Hunter, 2011) or growth in research funds (Shin, 2010). A second wave of PBF similarly was not found to have a statistically significant positive impact on retention rates or degree completion (Rutherford & Rabovsky, 2014; Umbricht, Fernandez, & Ortagus, 2017) and actually was associated with decreased access to higher education for traditionally underserved students (Kelchen & Stedrak, 2016; Umbricht et al., 2017).

As illustrated by the PBF state policy example, unintended consequences are an inevitable part of policy implementation, and populations experience impacts differently and in varying degrees. Institutional policies have created "challenges for students of color and their educational experiences" (Vue, Haslerig, & Allen, 2017)—the same logic could be applied to underrepresented faculty members. With RCM's spread throughout public higher education, my study aimed to provide a better understanding of RCM's relationship to faculty composition and compensation by gender and race/ethnicity.

Statement of the Problem

In this "era of hyperaccountability" (Knapp, 2009, p. 1), many public universities have implemented RCM as a strategy to increase revenue and transparency, track revenue and expenses, decentralize responsibility for cost savings and entrepreneurship, and fund strategic plans. Limited prior research on RCM has mainly focused on faculty and administrator perceptions of RCM (Allison, 2009), decision-making in the RCM environment (Cekic, 2008; Veldkamp, 2018), case studies of implementation experiences (Bouillon, Ehoff, & Smith, 2016; Hearn, Lewis, Kallsen, Holdsworth, & Jones, 2006) or single-institution outcomes (Pappone, 2016; Willett, 2013). Few studies, such as Jaquette, Kramer, and Curs' (2018) study of the effects of RCM on tuition revenue, have examined the relationship of RCM to outcomes or equity measures, such as faculty composition and compensation. Because of the lack of research on RCM, university administrators have implemented a policy that has had fairly little empirical investigations of its impacts and potential consequences.

Purpose of the Study

Despite unknown consequences and outcomes, RCM has spread throughout public universities. Studying the relationship between RCM, outcomes, and equity is an important next step for researchers. My study was grounded in the distributive justice and procedural justice tenets of organizational justice theory. Because RCM implementation is associated with increased decentralized decision-making power and budgetary responsibility, I aimed to gather insights on RCM as procedural justice (i.e., decision-making diffusion to deans or department heads) through distributive justice (i.e., salary amounts or proportions of who was hired by gender and race/ethnicity). I aimed to identify potential inequities in outcomes (faculty composition and faculty compensation) and inequities by gender and race/ethnicity within these outcomes associated with RCM implementation. This study examined the relationship of RCM with faculty composition and faculty salaries to determine if RCM implementation was associated with inequities in faculty salary or numerical proportions by gender or the intersection of gender and race/ethnicity at public, doctoral research universities broadly and for the engineering discipline.

Research Questions

My study examined the relationship between RCM implementation and faculty composition and compensation. To do this, I examined composition of assistant professors and salaries at public, 4-year, degree-granting doctoral universities, comparing institutions that implemented RCM between fiscal years 2012–2017 to institutions that did not. I also examined the institutional average salary equated to a 9-month contract for tenure track assistant professors, as well as their proportions by gender and by gender and race/ethnicity. I then examined the relationship of RCM implementation to proportions of assistant professors of engineering by gender and race/ethnicity. Finally, I examined the relationship of RCM implementation to annual salaries of engineering assistant professors. This quantitative study used difference-in-difference estimation to examine these relationships. The research questions were:

1. What is the relationship between RCM implementation and institutional average salary of assistant professors on the tenure track at public doctoral universities?
    a. when considering gender?
2. What is the relationship between RCM implementation and proportion of assistant professors on the tenure track at public doctoral universities when considering gender?
    a. when considering the intersection of gender and race?
3. What is the relationship between RCM implementation and the proportion of assistant professors of engineering at public doctoral universities when considering gender?
    a. when considering the intersection of gender and race?
4. What is the relationship between RCM implementation and the annual salaries of assistant professors of engineering at two public doctoral universities in Ohio?

Scope of the Study

This study was limited to public universities because of the more recent spread over the last decade of RCM budget models to public universities relative to private universities. Only those public universities that implemented RCM between FY2012 – FY2017 were considered in this study to allow enough time for the policy to have taken effect. The number of time periods (6 years) is appropriate both for this study and the difference-in-difference estimation method. Bertrand, Duflo, and Mullainathan (2004), in a review of 92 difference-in-difference empirical journal articles, found an average of 16.5 periods used, with 50% of the papers including 11 or fewer time periods.

I limited this study to the assistant professor rank to control for salary compression and because I expected the assistant professor rank to have the highest proportions of racially and ethnically diverse tenure-track faculty. Salaries of assistant professors increased at a rate (9%)

greater than associate professors (5.6%) because of the competitive compensation packages needed to lure these individuals to academia during the time period for which the study was conducted (June, 2014).

Although in 2017 the number of tenured/tenure-track assistant professors in all disciplines (7,373) fell far below full professor (13,882) but slightly higher than associate professor (7,266), the percentage of women at the assistant rank (24.3%) far exceeded full professor rank (11.8%) and associate professor rank (19.5%) (Yoder, 2017). African American and Hispanic assistant professors' percentages were slightly behind associate professors, but ahead of full professors, and Asian assistant professors had the highest percentage. Therefore, the assistant professor rank offered the most promising number of underrepresented tenure-track faculty members for the purpose of this study (Yoder, 2017).

A Note on Demographic Categories, Language, and Limitations of this Study

Like all research studies, this one had limitations in the design, instrumentation, and method. These limitations included demographic data collection procedures of the Integrated Postsecondary Education Data System (IPEDS) and American Society for Engineering Education (ASEE), secondary data analysis, comparing RCM models at different universities, and those limitations associated with the difference-in-difference estimation method. Limitations related to comparing RCM models and methods are addressed in Chapter 3: Methodology. In this chapter, I addressed some of the limitations of demographic data collection from IPEDS and the ASEE database.

I used several data sources for this study, each of which has unique methods of categorizing gender and race/ethnicity. When reviewing the literature, I use authors' language for gender and/or race/ethnicity when using direct quotes. When referencing data, I used specific instrument's categorizations and descriptions of variables.

Gender and sex assigned at birth. Binary categorizations for gender and sex assigned at birth were a limitation of this study. For example, although IPEDS uses "gender" as a demographic category, for faculty and staff, gender was only collected as a binary response option (man or woman). Strunk and Hoover (2019) defined gender as "a social construct, having to do with identity, gender presentation, physical and emotional characteristics, and the internal sense of self participants hold" (p. 199). Strunk and Hoover (2019) offered several ways adults may express gender identity in addition to man and woman: agender, nonbinary/genderqueer/genderfluid, two spirit, or another identity not listed. They also asked researchers to consider whether information was needed from participation on transgender identity, which they describe as typically referring "to individuals for whom their gender identity and sex assigned at birth are not aligned" (p. 199). None of the data sources used in this study collected this information. Although I personally subscribe to Strunk and Hoover's (2019) definition of gender, I was limited to studying faculty composition and compensation from a binary, static perspective because of data availability.

The ASEE database, another data source for this study, presented another data collection limitation regarding gender. ASEE recently added additional reporting options for gender for faculty and students for the 2019 survey to include Non-binary Gender/Another Gender or Unknown (American Society for Engineering Education, n.d.); however, these categorizations were not in place prior to this study. Additionally, ASEE conflated the gender category with biological sex response options. Strunk & Hoover (2019) differentiated between gender and sex: "sex is a biological factor, having to do with genital and genetic markers. In most cases, collecting data on gender is the more appropriate and sufficient option" (p. 198). Strunk & Hoover (2019) offered the following response options when collecting sex as assigned at birth: male, female, intersex, prefer not to respond. For the purpose of this study, I used the binary biological sex responses for faculty gender from ASEE as a proxy for gender (male to man, female to woman), recognizing that sex assigned at birth and gender identity are different, gender is fluid, and faculty identities may not align with these binary conceptualizations.

In addition to examining faculty composition and faculty compensation by gender, I also examined the intersection of gender with race and ethnicity, and due to the race/ethnicity categorizations of the United Sates (U.S.) federal government categories, citizenship. The race/ethnicity categories for IPEDS are presented in Appendix E, and the race/ethnicity categories for ASEE are presented in Appendix F. According to IPEDS, "Institutions MUST give students and staff the opportunity to self-report their race and ethnicity" (Integrated Postsecondary Education Data System, n.d.-a) including choosing not to respond.

Race and ethnicity. IPEDS and ASEE used race/ethnicity categories that aligned with the U.S. federal government categories. They included a category of "Nonresident Alien" which was defined as "A person who is not a citizen or a national of the United States and who is in this country on a visa or temporary basis and does not have the right to remain indefinitely" (Integrated Postsecondary Education Data System, n.d.-b)This data collection procedure did not allow for additional reporting on race/ethnicity for people assigned to the "Nonresident Alien" category.

U.S. definitions of race and ethnicity and the single response option were limitations of this study. Strunk and Locke (2019) define race as, "A designation based primarily on physical characteristics, including skin color. Can be thought of as the physical or biological differentiation, though genetic differences do not appear to exist" (p. 303). Strunk and Locke (2019) define ethnicity as:

> A designation based primary on social or cultural affiliation. Though related to race, ethnicity often includes finer distinctions, and is not based solely on physical characteristics, but social sense of belonging. In the US, the federal government defines ethnicity solely as "Hispanic" and "non-Hispanic," though that definition is not well aligned with scholarship. p. 298

When referencing literature, I used authors' terminology for race and ethnicity and when referring to IPEDS and ASEE data, I used the categorizations from the data sources unless otherwise noted. Race is a fluid, socially constructed concept, but because of the nature of available data, I was limited to studying race as a static designation and ethnicity as a binary designation, for which IPEDS and ASEE surveys only allowed single response options.

In addition to examining the composition and compensation of faculty across fields, I chose to conduct a more in-depth analysis of faculty within one specific field, engineering. In the engineering literature, the term "underrepresented minority" is prevalent, and it typically refers to people of color, except for Asian American and Pacific Islander persons. For example, Ong, Wright, Espinosa, and Orfield (2011) defined "underrepresented minority" women in STEM as African Americans, Chicanas/Latinas, and Native Americans. Although the authors included Asian American/Pacific Islander (AAPI) women among "racial ethnic minorities" and "women of color," AAPI women were not included in "underrepresented minority" women because they have not had the same low proportional representation in advanced STEM education and careers. In my own writing, analysis, and meaning making for this study, I borrowed from Harper (2012) and used the term "minoritized" rather than "minority":

> to signify the social construction of underrepresentation and subordination in U.S. social institutions, including colleges and universities. Persons are not born into a minority status nor are they minoritized in every social context (e.g., their families, racially homogeneous friendship groups, or places of worship). Instead,

> they are rendered minorities in particular situations and institutional environments that sustain an overrepresentation of Whiteness. p. 9

Therefore, in this study, I use “racially minoritized” rather than “underrepresented minority” recognizing that Asian American/Pacific Islander (AAPI) persons have been marginalized in certain settings of higher education, but they have not typically been underrepresented in the engineering discipline.

Significance of the Study

This study had policy and practice implications for higher education administrators at the central and decentralized (college and department) levels broadly, and for the engineering field, specifically. Policy implementation theory tells us that policies impact different groups disproportionately. The disparate impact theory of discrimination holds that employment discrimination occurred “when neutral policies or practices had a disproportionate, adverse impact on any protected class” (Equal Employment Opportunity Commission, n.d.), which includes women and racially minoritized persons. Therefore, it is critical to understand how institutional policies, such as RCM, impact employees in protected classes.

Central administrators, such as chief financial and budget officers and provosts, could use these research findings to inform decision-making efforts as they consider potential implications of implementing RCM budget models. Although RCM models share common core structures, they differ by institutions. Central administrators may find the results of this study reassuring that RCM models did not appear to negatively impact faculty salaries or proportions by race/ethnicity, with the recommendation that they conduct an internal study of their own RCM models to ensure inequalities do not persist at their institutions in light of formulaic differences or variations in decision-making across units at their universities.

As RCM is associated with an increase in decentralized decision-making and budgetary authority, college deans and sometimes department heads find themselves with more latitude over resource allocations. Although deans and department heads might also find this study reassuring that RCM models did not appear to negatively impact faculty salaries or proportions by race/ethnicity, they should similarly carefully examine their institution's RCM model to ensure inequalities do not persist at their institutions or for their colleges or departments. Additionally, although schools of engineering have been posited to fare well in RCM environments (Curry et al., 2013), during an exploratory analysis of salaries of assistant professors of engineering between two public research universities in Ohio, engineering deans and department heads, I did find noteworthy, albeit not significant, differences in the university that implemented RCM versus the university did not implement RCM. Future research is warranted at this college-level analysis of faculty salaries with a larger sample of institutions.

Organization of the Study

The rest of this dissertation is organized into four subsequent chapters. The theoretical framework that grounds the study, as well as the relevant literature informing the study, are reviewed in Chapter 2. The methodology, including the sample selection, variable selection, data collection, and data analysis procedures are described in Chapter 3. The results of the study are outlined in Chapter 4, and a discussion of the findings and implications for future research, policy, and practice are presented in Chapter 5.

Chapter Two

Theoretical Framework and Literature Review

Equity theory, which can be considered the balance of inputs (such as employee effort) and outputs (such as rewards) has long been used to study compensation (J. S. Adams, 1963, 1965; Goodman, 1974; Goodman & Friedman, 1971; Lawler, 1971; Weick, 1966; Weick & Nesset, 1968). Derived from equity theory (J. S. Adams, 1965), organizational justice theory has been used in fields such as industrial-organizational psychology, human resource management, and organizational behavior (Colquitt, Conlon, Wesson, Porter, & Ng, 2001). Organizational justice theory grounded this study by connecting the implementation of RCM model to the diffusion of decision-making throughout the organization and potential association with faculty composition and faculty compensation. An explanation of organizational justice theory, its tenets, and application to workplace and higher education research is outlined below. A review of the literature pertaining to the current higher education finance environment, RCM, faculty compensation, and the engineering discipline are then reviewed.

Theoretical Framework

Pay is primarily considered "a reward that can be used to make employees feel satisfied with their job, motivate them, gain their commitment to the organization, and keep them in the organization" (Lawler, 1971, p. 1). Aligning with the scientific management era of 1900–1939, early compensation studies often examined "piece rate incentive plans" but did not consider psychological implications of pay (Lawler, 1971, p. 7). A psychological frame of reference explained how “pay affects attitudes and behavior, and how [pay] can contribute to organizational effectiveness" (Lawler, 1971, p. 1). Pay signaled meeting security and physiological needs (Lawler, 1971) and the ability to acquire goods (Goodman, 1974), as well as recognition and self-esteem (Goodman, 1974; Lawler, 1971).

The 1960s and 1970s featured organizational payment studies grounded in equity theory (Greenberg, 1987), and during these decades many authors cited “the significance of equity considerations on allocations in organizations,” most of which emphasized the consequences of pay inequities (S. Alexander & Ruderman, 1987, p. 178). Adams (1965) defined inequity as:

> Inequity exists for Person whenever he perceives that the ratio of his outcomes to inputs and the ratio of Other’s outcomes to Other’s inputs are unequal. This may happen to either (a) when he and Other are in a direct exchange relationship or (b) when both are in an exchange relationship with a third party and Person compares himself to Other (p. 280).

An employee may evaluate one’s pay in relation to another through examining one’s input/output ratio in comparison to a colleague, system, such as a past bonus structure used at the company, or self, such as one’s role as a provider or a past position (Goodman, 1974). If inequity in pay exists, an individual will seek to reduce the inequity by reducing productivity or leaving the field (Adams, 1965). If one believes one is underpaid, for example, one might decrease inputs, thereby lowering the quantity and/or quality of work (Lawler, 1971). This observation was especially true for pay judged to be “unfairly low” or “unjustifiable” (Lawler, 1971, p. 99). Pfeffer and Langdon (1993) found that the wider the salary variation within academic departments, the “lower individual faculty members' satisfaction and research productivity” (p. 382). These early compensation studies offered a reason to explore faculty compensation under a new system, or RCM implementation, to determine if broad perceptions of resource allocation under RCM translated into inequities in faculty composition and compensation. Distributive justice and procedural justice, two tenets of organizational theory, provided a lens through which to examine resource distribution through faculty salaries in the current financial environment.

Procedural justice refers to the process, or means, whereas distributive justice refers to the outcome, or end (Alexander & Ruderman, 1987).

Distributive Justice

Distributive justice is the perceived "fairness in the distribution of resources" and recognizes that resources come in many different forms and can be distributed in many different ways, including through salaries and rank (Mahony, Hums, Andrew, & Dittmore, 2010, p. 94). From a distributive justice perspective, employee perception of fairness is correlated with employment outcomes, such as employee satisfaction. Distributive justice was found to be more important to pay satisfaction and job satisfaction than procedural justice at a Midwestern, public university (McFarlin & Sweeney, 1992). Other examples of distributive justice theory's use in higher education have included pay satisfaction (Folger & Konovsky, 1989), intercollegiate athletics (Andrew, Kim, Mahony, & Hums, 2009; Hums & Chelladurai, 1994; Mahony et al., 2010; Mahony, Hums, & Riemer, 2002; Patrick, Mahony, & Petrosko, 2008), job satisfaction among basketball coaches (Jordan, Turner, Fink, & Pastore, 2007), promotion and tenure, and resource allocation (Fitzgerald, Mahony, Crawford, & Hnat, 2014; Hnat, Mahony, Fitzgerald, & Crawford, 2015).

In an example especially pertinent to my study, Fitzgerald et al. (2014) used a distributive justice framework in their survey of 126 deans, school directors, and department chairs in a midwestern state at public and private institutions about the fairness of distributions of faculty compensation and other resources to units within the university. Participants judged salary distributions based on teaching and impact on students to be the fairest but acknowledged that decisions were more likely based on measures of research productivity. Participants did not believe that all faculty members should be paid equally, but rather pay distribution would be more equitable if it was based on both teaching and impact on students as well as measures of research productivity. Administrators at research institutions were more likely to perceive faculty compensation distributions based on measures of research productivity, such as publications and external funding, to be fairer and more likely than administrators at non-research institutions.

Also using a distributive justice framework, Hnat et al. (2015) interviewed nine academic deans from different disciplines about their decision-making processes about distribution of resources such as faculty lines, salary increases, and travel funds. They found five sub-principles of equity when applying the organizational justice theoretical framework to these resource allocation decision-making processes to assess employee inputs: (a) quantity and quality of research publications, (b) external research funding, (c) quality of teaching, (d) impact on students, and (e) quality service. Although expectations of quality and quantity of research productivity varied among deans and disciplines, consistently faculty who were judged to be more productive were considered more deserving of salary increases and travel funds. Some, but not all, deans pointed to external funding as important when determining research productivity. The deans who relied on student and peer evaluations of teaching as well as student work and performance to assess quality also valued teaching. Quality of service also was mentioned, especially when speaking about senior faculty members, as evidenced by collegiality, curriculum and program development, mentoring of junior faculty members, and community and professional service (Hnat et al., 2015).

Distributive justice and prior empirical studies grounded in it tell us that there are wide ranges of priorities, weights, and methods for distributing resources. Each decision maker has ideas of fairness of distribution, and recipients judge these distributions on perceived fairness. My study intends to offer insight on the faculty salary amounts that have been distributed and number of faculty (i.e., an outcome) at RCM institutions compared to non-RCM institutions to explore distributive fairness in each environment.

Procedural Justice

Employees judge an organization's fairness on more than the resources that are distributed; they also weigh the procedures by which resources are distributed. If these procedures are not transparent or are misunderstood, employees may perceive an organization to be unfair (Hnat et al., 2015). Procedural justice refers to "perceptions of the fairness of decision-making processes" (Folger, 1987, p. 178), including the "the fairness of the rules and procedures by which the rewards are distributed" (Alexander & Ruderman, 1987, p. 178). Although procedural justice has a stronger relationship to employee perceptions of organizational fairness than distributive justice (Alexander & Ruderman, 1987), it has been studied less in the workplace and in higher education.

Application of procedural justice to higher education included student evaluations of teaching. Tyler & Caine (1981) found undergraduate students relied on their perceptions of the fairness of the procedure the teacher used to grade work (procedural fairness) rather than their perceived fairness of the grade earned (outcome/distributive fairness) when "assessing their satisfaction with their teachers" (Tyler & Caine, 1981, p. 648). Additionally, Folger (1987) offered an illustration of a denied tenure case (outcome) to demonstrate that the faculty member felt "unusual and inappropriate" criteria (i.e., procedure) by which his research and teaching were evaluated were unfair. Procedural justice reminds us that faculty may hold the procedures and systems by which salaries are distributed to be just as much, if not more, important than the actual salary amounts earned. My study intended to offer insight on the equity of salary distribution procedures in RCM environments.

My study did not examine the relationship between distributive justice and procedural justice, but it was informed by both tenets. Existing empirical evidence related to legal (Walker et al., 1979), workplace (Folger & Konovsky, 1989), employee satisfaction (Alexander & Ruderman, 1987) and compensation (McFarlin & Sweeney, 1992) studies have demonstrated distributive justice and procedural justice are both independent and interrelated (Folger, 1987). For example, “although perceptions of procedural justice can influence perceptions of distributive justice, application of the fairest possible procedure does not define distributive justice” (Folger, 1987, p. 150). These prior studies justified framing this study within two tenets of organizational justice theory, distributive justice and procedural justice.

RCM encompasses formulaic elements of a budget system but also grants freedom and decision-making authority to responsibility center heads, typically academic deans. Although some may consider RCM to be a “neutral” policy, there are many actors and decisions that go into the design, implementation, and evaluation of the policy. The decision-making criteria and processes that deans and department heads use to make faculty hiring and compensation decisions are related to procedural justice. Gehl (2016) found evidence that increased department head discretion influenced pay inequities for foreign-born STEM faculty. According to procedural justice, one might expect to find inequities (perceived or real) in the decentralized decision-making autonomy granted to college deans and department heads and criteria used to distribute resources, such as faculty lines and salaries. On the other hand, distributive justice is represented by the salary amounts distributed to faculty and faculty members hired. Thus, according to distributive justice, one might expect to find inequities in faculty lines and faculty salaries, as well as inequities by gender and/or race/ethnicity. In this study, I examined the outcomes (faculty proportions and faculty salaries) to gain insight as to the distributive fairness of RCM implementation for faculty composition and faculty compensation.

Review of the Literature

There were several bodies of literature pertinent to this study, including RCM and other common types of university budget models and how resources have been allocated and distributed under each. Faculty composition, faculty compensation, and disciplinary, gender, and racial differences were also discussed.

Higher Education and Policy Environment

The current higher education environment is focused on accountability and cost containment, which has led to an increased use of RCM at public universities. Related to concerns over rising tuition and fees are concerns over rapidly rising costs. The real cost of a college degree has risen rapidly since the 1980s (Archibald & Feldman, 2008). Colleges are highly regulated by federal and state governments, and some mandates are required to be carried out with little or even no funding provided by the federal or state government. The Secretary of Education stated that as many as twelve different federal agencies increase costs to higher education through regulations surrounding financial aid, research conduct, and admission of foreign students, many of which are unfunded mandates (Dickeson, 2006). Cost escalation in higher education has been categorized by regulation, micromanagement, and cost shifting; cost disease; the desire to generate new knowledge while acknowledging the relevance of old knowledge; an increase in administrative and academic support staffs; and faculty output creep beyond teaching and advising (Massy & Wilger, 1992).

As the revenue theory of cost explains, “the dominant goal of institutions are educational excellence, prestige, and influence” (Bowen, 1980, p. 19). Faculty members are central to creating new knowledge and educating students. Faculty wages are often blamed for increasing higher education costs, but research findings about the relationship are mixed (Bipartisan Policy Center, 2017). Cost disease theory, often attributed to Baumol (1967) and Baumol and Bowen (1966), explains that labor productivity resulting from technological progress does not apply to service industries, such as higher education. Industries such as higher education find difficulty in increasing productivity without compromising quality (Archibald & Feldman, 2008; Massy & Wilger, 1992). However, overall faculty wages have not changed significantly from 2000–2012 because tenure-track positions, which once made up 80% of college faculty, have been reduced to 34%, while the reliance on lower-paid part-time faculty numbers have increased (Bipartisan Policy Center, 2017). These changes in the higher education finance and policy environment have left many university administrators seeking a new budget model that can respond to this resource-constrained, dynamic environment.

Centralized University Budget Models

Incremental budgeting and formula-based budgeting are two types of centralized budget systems commonly used in higher education. Centralized budgeting systems place decision-making power at the central level, such as with the provost or chief academic officer of the institution. In the current higher education environment with shrinking state funds, RCM may afford revenue centers more flexibility to respond quickly to market conditions, as well as create incentives for entrepreneurial behavior by allowing units to identify new revenue streams for which they are able to use a high portion of the profits at their discretion.

Incremental budgeting. Although RCM use among institutions of higher education is growing, the most common form of university budgeting is incremental budgeting (Curry et al., 2013; Goldstein, 2012; Hillman, 2016). Under incremental budgeting, each unit has a “base” budget, and each year new funds may be requested on top of that base layer from central administration. Unrestricted revenue, such as tuition, investment income, and unrestricted gifts, are controlled centrally. This model provides a lot of decision-making power to central administration and is simple to manage. It is also widely accepted to be efficient and fair (Goldstein, 2012).

Formula-based budgeting. Formula-based budgeting is also common centralized budget model. However, policy formulas are designed based on inputs or outputs, such as enrollment, research activity, or graduation rates (Curry et al., 2013). Formula-based budgeting is used by 26% of higher education institutions (Green, Jaschik, & Lederman, 2011) and is more adaptable to changing environments than incremental budgeting. The most common formula used "is a credit-hour weighting to account for differential delivery costs of instruction" (Curry et al., 2013, p. 16).

Incremental budgeting and formula-based budgeting lack the environment to create several conditions that RCM attempts to address. Incremental budgeting does not allow decision makers to adapt quickly to new environments or opportunities, and the system has a work burden for central administrators (Curry et al., 2013). Incremental budgeting is not conducive to strategic planning, adapting to build on university strengths, or pursuing the university's mission and vision (Goldstein, 2012). Formula-based budgets do not work well with all academic activities, such as research and service, and it is difficult to create formulas that are neither too simple nor too complicated, remain fair, and offer valued incentives (Curry et al., 2013).

RCM: A Decentralized Budget Model Alternative

Incentive-based budgeting models, such as RCM, are decentralized and have placed more decision-making power and responsibility to revenue center administrators, such as college deans, administrative vice-presidents, or even department chairs, when revenues and expenses were allocated directly to those units. Unlike incremental and formula-based budgeting, RCM facilitates a) entrepreneurial behavior, b) explicit allocation of indirect costs, c) differing instructional costs among schools, and d) placing revenue variances and responsibility at the unit level (Curry et al., 2013). RCM names and models have varied across institutions; but many of the underlying principles of RCM remained consistent, including attributing costs and incomes to respective units (incorporating appropriate incentives for units to increase income and reduce costs), and requiring units to pay for support units, such as the library or counseling (Whalen, 1991, p. ix). According to Curry et al. (2013),

> "RCM was developed and has evolved over some 35 years in response to multiple forces: changes in the external environment - the larger economic context; needs within universities to achieve a balance between academic authority and financial responsibility; desires to unleash and provide structure to entrepreneurship; the need to have realistic measures of the quality, cost and growth of administrative services; and the increasing imperative to understand the full costs attending academic programs" (p. 11).

There is much to learn about how resources are distributed within institutions of higher education (Hnat et al., 2015; Santos, 2007; Volk, Slaughter, & Thomas, 2001). In higher education, "ideas for programs and services to advance the institutional mission . . . seem limitless, whereas resources are always finite (Barr & McClellan, 2018, p. 63). In RCM environments, "an equitable distribution of funds is needed that [recognizes] the diversity of institutions, programs and students" (Zierdt, 2009, p. 350). RCM utilizes a decentralized approach to budgetary decisions, which "takes advantage of the knowledge resident at the forefront of programs and services" (Barr & McClellan, 2018, p. 90). RCM models are difficult and time-consuming to design and implement (Barr & McClellan, 2018; Lang, 1999). The design of an RCM budget model typically includes formulas for revenue and cost allocations, as well as a strategic incentive fund for central administration. Most RCM models have created similar organizational structures, where units have been described as a revenue center, cost center, or central administration, and most models have allowed for some type of central fund to steer university-wide strategic planning.

Revenue allocation under RCM. In public institutions of higher education, revenue has included state appropriated funds, tuition, mandatory student fees, endowment income, special student fees, gifts, grants and contracts, auxiliary services, special programs, contracted institutional services, and licensing, patents, and royalties (Roos & Gatta, 2009). Under RCM, tuition revenue has typically been a key component of revenue allocation, such as through a formula based on student credit hours or student full-time equivalent (FTE) based on enrolled major. Revenue centers have been able to generate revenues, retain control over these revenues, and pay for their costs, both direct and indirect (Goldstein, 2012). Revenue centers typically include academic colleges and research centers. Whalen (2002) described these centers as "independent - but not autonomous - fiscal entities within an institution: little universities within a university universe" (p. 11).

Expense allocation under RCM. Common expenses in public higher education institutions have included salaries, benefits, program supplies, office supplies, equipment, utilities, communications, programming, professional development, memberships and periodicals, travel, entertainment and gifts, facilities, utilities, contracted services, debt service, scholarships and fellowships (Barr & McClellan, 2018). Instruction has been considered the most important educational and general expense category and includes teaching salaries (Goldstein, 2012). Under RCM, revenue-generating units have paid for the services of non-revenue generating units, such as the Office of the Vice President for Research (Pappone, 2016). Assigning costs to these services and products has incentivized revenue-generating units to use them responsibly and make sound financial decisions (Whalen, 1991). These assigned indirect costs must be transparent and easily understandable by units making decisions (Lang, 1999).

All costs are allocated to revenue centers under RCM, including direct and indirect costs. This allocation removed "the illusion of free goods and services-goods and services which appear free to operating units but which are not free to the institution" (Whalen, 1991, p. 50). Direct costs can be associated with specific activities, but indirect costs can be more difficult to connect to users. Therefore, institutional structures for cost sharing for service categories such as academic support, student services, physical plant, and central administration are typically developed, and "assessments are employed to cover the public goods or public service aspect of support services; charges, to cover the portion of support services which is marketable" (Whalen, 1991, p. 51). Taxes are assigned to revenue centers based on a formula, and payment is mandatory. This formula might be based on student credit hour enrollment or space occupied by a center, for example. Alternatively, "charges are payments for services provided by a support center specifically for a user" (Whalen, 1991, p. 51). The user can purchase more of the service for additional payment or decline the service and not pay a charge (Whalen, 1991). A cost center also can incur expenses and not generate revenues on its own but rather be funded "from central revenues and taxes assessed on revenue centers" (Goldstein, 2012, p. 97). A cost center might fund its services through "charge-back mechanisms," fees for services rendered based on pre-established rates (Goldstein, 2012, p. 98), or revenue centers may pay their share of areas such as the library or human resources.

Incentivizing institutional priorities under RCM. In contrast to the for-profit world, where RCM originated, "maximizing profit or shareholder value is the objective . . . In the university world, the objective is maximizing 'academic profit'-typically measured in terms of achieving the university mission through instruction, knowledge development, and service" (Curry et al., 2013, p. 29). Although RCM is a decentralized budgeting system, some level of centralization is needed for institutional coordination and strategic planning. RCM aimed to "decentralize budget-making authority without abandoning institutional-level values and priorities" (Massy, 1996, p. 5). Centralized university administrators may have trouble compelling individual units to align with institutional goals (Hearn et al., 2006) without enough central funding. However, allocating too large a percentage of revenues to units reduces central administrators' ability to fund strategic initiatives adequately (Curry et al., 2013).

Under RCM, central administrators have retained discretionary funds to incentivize strategic university priorities, called "subventions" (Pappone, 2016). This subvention, or tax, has leveraged the leadership of central administrators, such as the president and provost, to guide strategic priority areas for the institution (Whalen, 2002). This central tax has created "a subvention pool that funds cost centers as well as revenue centers that don't generate enough revenues to be self-sufficient" that is collected and distributed by central administration (Goldstein, 2012, p. 98). RCM has used subvention "to achieve balance between local optimization and investment in the best interest of the university as a whole" (Curry et al., 2013, p. 17). If administrators have transparently communicated institutional priorities, RCM has explicitly recognized these through subversions through the RCM model (Curry et al., 2013, p. 125).

Advantages of RCM. Several advantages of RCM are cited by its proponents. These include the incentivization of entrepreneurial behavior, explicit allocation of indirect costs, allowance for differences in costs of instruction, and placing responsibility at the revenue center (typically an academic college within an institution) level.

Entrepreneurial behavior. RCM encourages entrepreneurial behavior (Goldstein, 2012; Lang, 1999), as it helps leaders recognize good and non-performance and reveals institutional strengths through inter-unit competition (Hearn et al., 2006). Faculty and staff at college and departmental levels are increasingly involved in generating revenue from tuition and fees and public and private gifts, grants and contracts, and the sales of services (Whalen, 2002). RCM is intended to support an entrepreneurial environment that promotes unit revenue generation with the incentive of the ability of revenue centers to be able to retain the income they generate (Whalen, 2002). Disciplines with a close tie to industry, such as engineering, have had the most success with faculty entrepreneurism (Lee & Rhoads, 2004). Under RCM, faculty can "exercise their considerable authority responsible for the benefit of themselves, their students, their organizational units, and the institution as a whole" (Curry et al., 2013, p. 25). At times, subventions are used to encourage entrepreneurial behavior through start-up funds (Strauss & Curry, 2002).

Explicit allocation of indirect costs. RCM is ideally suited for large, complex institutions (Curry et al., 2013; Massy, 1996). RCM has made transparent institutional priorities by explicitly identifying "subversions" from system allocations to fund these initiatives (Curry et al., 2013). Pappone (2016) found increased transparency in the flows of revenues and expenditures, and the review committee at University of Indiana-Bloomington concluded "the transparency of the budgeting process under RCM has enabled good use of scarce financial resources" (*Responsibility centered managment at Indiana University Bloomington*, 2000, p. 15). RCM has made costs explicit, so faculty and staff appreciated the value of overhead costs and were more likely to optimize space and other resource usage (Goldstein, 2012). RCM eliminated "the notion of 'free goods' for faculty and departments" and led to better stewardship of resources (Priest, Becker, Hossler, & St. John, 2002, p. 4). RCM also helped decision-makers compare margins to understand the direct and indirect costs of a growth or decline in programs. By tracking indirect administrative and service costs, RCM has helped administrators determine how these costs are shared within the university and which services are prioritized (Pappone, 2016), as well as how administrative efficiencies were enhanced (Hearn et al., 2006). RCM has encouraged "non-self-sustaining academic units - such as administrative services - to act responsibly" (Strauss & Curry, 2002, p. 27) and has helped reduce administrative costs at the University of Pennsylvania and University of Southern California (Strauss & Curry, 2002).

Differing instructional costs across units. Proponents of RCM have cited benefits to students, faculty, and administrators. Proponents of incentive-based budget systems, such as RCM, have argued that the system forces decision makers to keep students in the forefront, as they are primary customers and revenue generators (Hearn et al., 2006). RCM has allowed administrators to make comparisons across units, for example, to compare instructional costs of academic programs (Pappone, 2016). For example, according to a report by the National Bureau of Economic Research, the cost of delivering electrical engineering in the United States was 109% greater than English, and the field of mechanical engineering did not offset high faculty salaries by increasing class sizes as did some other disciplines (Valbrun, 2018). Under RCM, revenue centers have been responsible for their own instructional costs.

Placing revenue variances and responsibility at the unit level. RCM has encouraged revenue enhancement (Goldstein, 2012; Massy, 1996) and allowed academic colleges "to benefit directly and immediately from their own revenue increases and cost savings" (Hearn et al., 2006, p. 288). Under RCM, administrators have efficiently allocated resources to those with decision-making authority and responsibility and provided a foundation for administrators to be able to analyze data to inform decision-making and effective planning (Hearn et al., 2006). RCM has helped administrators understand how funds flow throughout an institution, which allows administrators to know which units contribute revenue to institutional operations in excess of their costs. During an institutional review of its RCM model, the review committee at University of Indiana-Bloomington found “RCM provides incentives for units to monitor their performance, with the goal of increasing efficiency and effectiveness” (*Responsibility centered managment at Indiana University Bloomington*, 2000, p. 15).

Limitations of RCM. Although proponents of RCM have cited several weaknesses of centralized budgeting systems that RCM attempts to address, RCM has its limitations. Limitations of RCM relate to the design of the budget management system, inter-unit competition, educational quality, and system responsiveness have been cited.

Inter-unit competition. RCM is perceived to promote inter-unit competition for students and resources (Barr & McClellan, 2018; Whalen, 1991), and Pappone (2016) found evidence of internal competition for students and credit hours. Pappone (2016) found mixed perceptions about the relationship between RCM and interdisciplinary teaching and research, with some faculty and administrators perceiving additional barriers to interdisciplinary collaborations and otherings thinking these barriers existed prior to RCM implementation. Units may not encourage students to study outside of the unit, such as through obtaining a minor or double major in another area, to keep the course revenue. Instead, units may offer revenue-making courses contrary to the unit’s mission and purpose, resulting in an inefficient, duplication of courses. For example, although a unit may find it advantageous to create its own service if able to do so at a cheaper rate than is available through a central service, that decision may positively impact that unit but negatively impact other institutional units by increasing their share of the central service.

Tension may also increase between academic and administrative units. Academic units may question the efficiency of service centers (Whalen, 1991) since they pay for service units without significant say in their operations (Hearn et al., 2006). Zierdt (2009) found mixed results that RCM was related to perceived barriers to interdisciplinary teaching and research.

Educational quality. Other concerns may also affect the quality of student education. Units may look to increase revenue by eliminating majors and programs with low student enrollments (Adams, 1997; Wilms, Teruya, & Walpole, 1997). Critics of RCM fear decreases in academic quality through lower admission criteria, grade inflation, and decrease in academic quality. No clear empirical evidence exists of RCM positively impacting student learning outcomes and educational quality, and Rhoades and Slaughter (2004) cautioned:

> "One relatively indirect form of shaping the curriculum lies in a system of budget allocation mechanisms and incentives that involve turning the academy internally into a competitive marketplace for centrally allocated resources…The incentive is to move toward curricular offerings and delivery systems that maximize student numbers and cost efficiencies, even if they are at the expense of educational quality considerations." (p. 48)

For example, units may look to increase revenue by decreasing faculty or increasing teaching loads (Adams, 1997; Wilms et al., 1997). RCM also has limitations related to faculty hiring and, indirectly, compensation. Kirp (2003) found a change in faculty hiring practices to increase student enrollment at the University of Southern California following RCM implementation by hiring faculty with "little sense of the profession but could give bravura lectures that appealed to undergraduates" (p. 119). Although RCM is intended to benefit entrepreneurial activity of faculty, "any prediction of how a faculty member may or may not respond to a competitive reward structure versus a fixed merit standard, depends on the faculty member's position in the outcome distributions, how accurately the outcomes are measured, and the faculty member's behavior toward risk" (Priest et al., 2002, p. 6).

System responsiveness. System responsiveness includes ability of the system to incentivize strategic priorities, ability to accommodate unplanned costs and revenue, and responsiveness to external and internal climate. The external environment may influence the effectiveness of RCM in handling unplanned costs. A faculty committee report commissioned by the university president found RCM to be unable to respond to units in crisis (*Responsibility centered management at Indiana University Bloomington*, 2000). Some units perceived lost decision-making power and autonomy as central administrators set taxes/rates for service units and create incentives that reinforce university objectives. If these rates were not consistent or if colleges absorbed unanticipated costs, deans found budget planning challenging. For example, one Minnesota dean felt the system shifted "under our feet year after year" (Hearn et al., 2006, p. 303).

Decentralized Decision-Making and RCM. In the RCM environment, budgetary decision-making is pushed out to the college, and sometimes department, level. Under a system such as RCM, deans are considered university presidents' allies (Whalen, 1991, p. 21). RCM distributes some of the opportunities, challenges, incentives, responsibility, and authority formerly held by central administrators to the heads of revenue centers, college deans and sometimes department chairs. Unique to RCM environments, deans are responsible for increasing revenue and decreasing expenses within the units for which they have responsibility (Strauss & Curry, 2002; Volpatti, 2013; Whalen, 1991). Deans, as heads of responsibility centers, "make decisions that are congruent with the interests of the entire institution as well as with the interest of their unit" under successful RCM models (Whalen, 2002, p. 11). Deans prepare budget proposals for their units projecting budget revenues and indirect costs, and typically these are discussed periodically with central administrators, such as the CFO and provost (Curry et al., 2013).

Under RCM, Lang (1999) likened deans to CEOs who are not prepared for nor want to assume such financial decision-making responsibilities. Deans or department heads may be challenged to look beyond their own best interests and local priorities to broader institutional objectives (Cantor & Courant, 2003; Hearn et al., 2006). Under RCM, deans are forced "to determine their most valuable programs on both a qualitative and financial bottom line basis. If programs are low in quality and high in subsidy, the opportunity costs of protecting them are high. Quantifying such opportunity costs enables the case for change" (Curry et al., 2013, p. 95). These heads of revenue centers are responsible for increasing revenue and decreasing expenses within the units for which they have responsibility within RCM environments (Curry et al., 2013; Hearn et al., 2006; Volpatti, 2013; Whalen, 1991). Models similar to RCM have been described as "embodied in the state of mind, an attitude, of both central administration and center heads that they are empowered to make decisions" (Whalen, 2002, p. 11).

Although RCM is increasingly popular and proponents have offered several advantages over traditional incremental and formula-based budgeting models, little is known about the outcomes of this budget model. RCM has been critiqued for its time-consuming design, potential for inter-unit competition, neglect of educational quality, and inability of the system to respond during a crisis. However, the design and flexibility of RCM, opportunities for strategic planning through subvention, and the decentralized decision-making power of deans offer opportunity for administrators to tweak existing systems to improve outcomes based on institutional experience and research findings. Proponents of RCM believe that administrators who have the best understanding of units, such as deans, should make the decisions regarding those units.

RCM shifts decision-making power to deans, so those decisions “may rest on a myopic perspective that is not tightly linked to broad institutional priorities” (Barr & McClellan, 2018, p. 90). Deans may not desire or be prepared for the decision-making power they receive under RCM (Hanover Research Council, 2008; Whalen, 1991). RCM typically increases focus on revenues (Curry et al., 2013), and in pursuit of revenues, deans may favor short-term planning over long-term planning. RCM is a long-term strategy that requires patience for implementation, and perhaps even new administration, as opposed to a short-term response to financial problems (Lang, 1999). One Indianapolis dean shared his experience under RCM: “Power. I have never had such power. I’ve been in charge of large federal agencies and served as dean at other schools, but this kind of discretion has not been available to me. It’s almost scary” (Whalen, 1991, p. 144). Resource distributions through faculty tenure-track lines and faculty salaries are two examples of decisions typically influenced, at least in part, at the college dean and department head levels, meaning faculty composition and compensation is an RCM environment is unique due to increased decentralized decision-making. Environments with increased discretionary decision-making among department heads are associated with larger racial pay gaps among White and African American STEM faculty (Ghel, 2016). Understanding this potential limitation of RCM budgeting is where my dissertation research contributes to the RCM literature most explicitly.

Faculty Compensation

The study of compensation is important because “pay is usually the job aspect within which the greatest number of employees express dissatisfaction” (Lawler, 1971, p. 219). Consequences of dissatisfaction with pay include poor job performance, strikes, grievances, turnover, and job dissatisfaction (Lawler, 1971). Relevant to faculty satisfaction, Lawler (1971) found that higher levels of education relate to greater feelings of pay dissatisfaction. Similarly, Faculty compensation offers an "odd mix of annual merit- and non-merit-based salary increases, reflecting adjustments for promotions, longevity, market conditions, price level changes, and pure merit" (Hansen, 1988, p. 115). Institutions are responsible for demonstrating compensation through a merit system or seniority system that includes standards that are objective and applied consistently in a non-discriminatory manner (Eisenberg, 2010). In practice, however, universities often award salaries and salary increases using ambiguous and subjective means (Wallace & King, 2013), and faculty members are often frustrated by a lack of transparency in performance measures and compensation (Carson, 2013).

There are many predictors of faculty compensation identified in empirical studies at the regional, institutional, and individual levels. Examples of regional or statewide characteristics that have had a relationship with faculty salaries include geographical location and political representation. Examples of institutional predictors have included sector, Carnegie Classification, and unionization. Individual predictors have included research productivity and socially constructed demographic characteristics of faculty members, such as gender and race/ethnicity.

Institutional predictors of faculty compensation. Although faculty compensation studies are often grounded in a human capital theory framework and use individual predictors of salary, such as research productivity, critical quantitative inquiry encourages the exploration of "factors not typically included in traditional quantitative analysis" (Stage, F. K. & Wells, 2014, p. 5). Focusing solely on individual level predictors of faculty salary has failed to account for critical perspectives on how departmental administrators and expectations influence faculty behavior (Santos, 2007). Renzulli, Reynolds, Kelly, and Grant (2013) suggested "institutions, as employers, have the most immediate impact on faculty rewards, including pay" (p. 60). Research has demonstrated relationships between faculty salaries and institutional characteristics, such as sector, institutional type, Carnegie Classification, research activity, unionization, and other financial measures of institutional wealth. These predictors and their relationships to faculty salaries, both generally and within the engineering disciplines, are outlined below.

Doctoral universities and research activity. Faculty salaries have differed based on institutional type (Luna, 2007; Renzulli et al., 2013), but research behaviors are valued at most institutional types (Fairweather, 1995). The Carnegie Basic Classifications have differentiated between level of research activity at doctoral universities. In 2016, doctoral universities with highest research activity employed 34,515 assistant professors, whereas 19,104 assistant professors were employed at higher research activity and 10,389 were employed at moderate research activity universities. In 2015, salary expenditures at doctoral universities with highest research activity totaled $17.6 billion to 153,873 instructors, which comprised 49.5% of their overall expenditures for a median institutional expense of $667 million. Salary expenditures at doctoral universities with higher research activity totaled $6.09 billion to 69,182 instructors, which comprised 45.2% of their overall expenditures for a median expense of $190 million. Salary expenditures at doctoral universities with moderate research activity totaled $2.99 billion to 37,843 instructors, which comprised 43.1% of overall expenditures for median institutional expenses of $70.6 million (DATAUSA, n.d.).

Women faculty at public, doctoral institutions earned approximately 8% less salary than men in 2017–2018 (American Association of University Professors, 2018); doctoral institutions have the largest gender salary gap relative to other institutional types (Meyers, 2011). Women assistant professors outnumber men of the same rank at moderate research activity institutions, but assistant professors who are men outnumber women at highest and higher research activity doctoral institutions (DATAUSA, n.d.).

Unionization. The Wagner Act of 1935 was the first federal law to allow unionization in the private sector, and it established the National Labor Relations Board (NLRB). In 1970, the NLRB added private, not-for-profit institutions of higher education to its jurisdiction. Finally, the Taylor Law of 1967 granted public employees the right to unionize, which extended the use of collective bargaining to public higher education (Springer, 2009). Unionization requires institutions to review and establish democratic compensation practices, such as salary steps (Benjamin & Mauer, 2006). Collective bargaining or union control has been shown to impact faculty salary differences in some studies (Clery, 2015; Ogun, 2016), but not all (Gomez-Mejia, 1992). Unionization has also varied by geographic location; “two thirds of all unionized faculty are located in five states that have historically been supportive of organized labor: California, New York, New Jersey, Illinois and Michigan” (Griffey, 2016, para. 4). My study included unionization as a covariate to capture collective bargaining presence.

Other financial and regional predictors of salary. Other measures of institutional wealth and prestige, such as financial resources, revenue per student, endowment per student, and higher institution selectivity with lower admissions rates, have positively correlated with higher faculty salaries (Rippner & Toutkoushian, 2015). Environments surrounding institutions have also affected faculty salaries. Geographical location (Ogun, 2016), regional variations in cost of living, and political representation, or the relationship with state appropriations to higher education, have also impacted faculty salary differences (American Association of University Professors, 2018). My study captured such regional differences as covariates. Differences in faculty compensation have also been identified at the individual level.

Individual predictors of faculty compensation. Research has demonstrated relationships between faculty salaries and individual characteristics such as academic discipline, research productivity, and rank, as well as social identity constructs, such as gender and race. The relationship with salaries has been dependent on the sum and interaction of relevant factors. For example, the relationship between gender and salary has varied among academic disciplines.

Research productivity. Research productivity has consistently been one of the most significant predictors of faculty compensation. Research influence, as measured by quantity of publication citations, has been a primary predictor of faculty salary (Hilmer, Ransom, & Hilmer, 2015), as has number of articles published over one's career (Hensley, 2014) and book publications (Stack, 2014). Furthermore, citation rates have correlated more with salary than seniority (Grofman, 2009). Although years of teaching experience positively correlates with faculty salary (Stack, 2014), faculty whose primary activity is teaching are paid less than faculty whose primary activity is research (Meyers, 2011). However, deans have varying expectations of quantity and quality of scholarly productivity when allocating resources in RCM environments (Hnat et al., 2015). Deans are more likely to consider research productivity and grant funding to compensate faculty and allocate resources, even though they believe resource distribution according to teaching quality and impact on students would be fairer (Fitzgerald et al., 2014).

Relationships between bias, campus climate, and research productivity have been established. (Rosser, 2004) (as cited in Eagan & Garvey, 2015) noted "although women publish and present at similar rates as men, their colleagues tend to overlook their research achievements due to gender bias" (p. 929). Women have heavier teaching, mentoring, and service loads than men faculty (Eagan & Garvey, 2015). Women and racially minoritized faculty also experience greater amounts of gender and race-based microaggressions in academia, which results in higher stress levels. For women of color, the significant stress levels correlate with lower levels of scholarly productivity (Egan & Garvey, 2015). Throughout their journey through earning tenure and being promoted to full professor, Black women consistently faced gendered and racial microaggressions, and were constantly asked to defend their research expertise (Croom, 2017).

Rank. Departmental resource allocations for faculty salaries have depended on the distribution of faculty ranks, and salaries are lower for junior faculty (Goldstein, 2012). Full-time employment status (Hensley, 2014) and faculty rank (Hensley, 2014; Luna, 2007) have been significant predictors of faculty salary. Hansen (1988) found that an increase in rank, or a promotion, "almost without exception brings with it an above-average salary increase" (p. 115).

Gender. Many studies about the gender earnings ratio are grounded in Human Capital Theory (Erosa, Fuster, & Restuccia, 2016; Gómez Cama, Larrán Jorge, & Andrades Peña, 2016; Lips, 2013a, 2013b; Manning & Swaffield, 2008), although this perspective does have its limitations, as addressed by feminist economists and sociologists. Human capital theory is used to explain away discriminatory systems and behaviors in pay by gender (Lips, 2013b) with "roots in system-justification beliefs . . . reinforced by a human capital approach, which may appear to rationalize the gender pay gap by attributing it mainly to the choices individuals make, while downplaying the role of discrimination" (Lips, 2013a, p. 223). The pay gap exists even "after controlling extensively for 'choice' factors such as education, actual work experience, training and family characteristics" (Eisenberg, 2010, p. 27). Full-time or part-time work, occupational choice and occupational segregation, educational investments, work experience and continuity, expectations, values, stereotypes, and social capital are all explanatory variables not addressed by the human capital theory (Lips, 2013a). Conceptualizing the gender gap through distributive justice and procedural justice frameworks offered an alternative approach to human capital theory.

In the United States, in nearly every occupation, men make more money than women (Joint Economic Committee Democratic Staff, 2016; Levine, 2016). Women with advanced degrees make 26% less than men with advanced degrees (Levine, 2016). As much as 40% of the pay gap is attributed to discrimination (Joint Economic Committee Democratic Staff, 2016), and academia is no different when it comes to the salary gap. Faculty salaries in higher education are reflective of the gender earnings ratio that exists between men and women in other occupations.

Race. In a review of literature covering 1988–2007, Turner, González, and Wood (2008) analyzed 252 publications related to faculty of color. Lack of racial diversity among faculty composition was an overwhelmingly common theme, and salary inequities and promotion and tenure concerns also emerged. In a qualitative study of law school faculty members who are minorities, Carson (2013) found faculty "compensation schemes have skewed total compensation in favor of" White men (p. 62). In the United States, women of color make substantially less than White women (Joint Economic Committee Democratic Staff, 2016; Levine, 2016).

Academic discipline. Academic discipline plays a major role in determining salary (Stack, 2014). Women faculty members are more significantly concentrated in disciplines with lower market values than men (Luna, 2007). Disciplines such as engineering, especially at research institutions, where faculty are well-known within and outside of their institution for scholarly research activity and published research papers and presentations, are subject to external market forces:

> "Market adjustments recognize differential changes in the supply-demand condition by discipline, and even subdiscipline, in the average levels of salaries required for

> institutions to remain competitive, and in what it takes to retain existing faculty members and to recruit new faculty members, both within the academic and the larger non-academic labor market." (Hansen, 1988, p. 116)

This external demand for advanced engineering degree holders was one reason I was interested in further studying faculty composition and compensation in the engineering discipline.

Faculty Composition and Compensation in Engineering

Although the United States has lagged behind 15 other countries in global standings for the number of engineering graduates produced, it leads globally in rankings of engineering and technology education with 31 engineering departments in the Top 100 *Times Higher Education* rankings (Centre for Economics and Business Research, 2016). However, advanced degree holders in engineering are in high demand by the industry sector, which pays higher than academia. Academia faces increasing competition from industry for engineering graduate degree-holders who might otherwise seek an academic faculty career. Although 76% of doctoral students begin their studies intending to pursue an academic career, only 52% maintain that interest, and 24% of engineering doctoral students originally intending to pursue academia lose interest over the course of their studies (Roach & Sauermann, 2017).

Lack of diversity in engineering. Adding another layer of complexity for university administrators is the lack of compositional diversity of women and historically racially minoritized groups at every level of engineering education. Although engineering faculty and students are increasingly in demand, the lack of compositional diversity of the discipline is concerning to the profession.

Women are considered an underrepresented population in engineering (National Science Foundation & National Center for Education Statistics, 2017; Sowell, Allum, & Okahana, 2015) and are outnumbered by men. Across all science and engineering fields, men are more likely to pursue a PhD in engineering than women, fewer women intend to pursue a career in academia, fewer women remain interested in academia after beginning their studies, and a slightly higher percentage of women are more likely to lose interest in academia completely throughout their studies (Roach & Sauermann, 2017).

Even though there was a higher increase in bachelor's degrees in engineering being conferred from 2011–2016 (42%) relative to all other majors (11%), racially minoritized students remain underrepresented among engineering degree completers compared to the percent of college graduates in their demographic groups (Anderson, Williams, Ponjuan, & Frierson, 2018). The small percentages of racially minoritized students enrolled in and completing engineering graduate education is also concerning to the future of engineering education. Master's degrees in engineering conferred to Black graduates increased at a lower rate (6%) compared to all other degrees (10%) conferred to Black graduates from 2011–2016 (Anderson et al., 2018). From 2008-2013, African American, American Indian, Asian, and Hawaiian/Other Pacific Islander engineering doctoral student enrollment *decreased*, and Latino engineering doctoral student enrollment increased by less than one percentage point (McGee, Robinson, Bentley, & Houston, 2015). Between 2011–2016 the percentages of master's and doctoral engineering degrees earned by racially minoritized groups (not including Asian American) stayed stagnant at 2% each, despite numerous national efforts to broaden participation in engineering graduate education (Anderson et al., 2018). The 10-year PhD completion rate for racially minoritized students (Black/African American, Hispanic/Latino, Native American/Alaska Native) is only 56% in engineering as compared to 63% in the life sciences (Sowell et al., 2015). Racially marginalized women have a 56% STEM doctoral completion rate, which is slightly higher than racially marginalized men (52%) (Sowell et al., 2015).

Even though the number of engineering faculty increased between 2008-2013 and even with investments in diversifying the faculty, racially marginalized engineering faculty growth has been slow to nonexistent (McGee et al., 2015). From 2003-2013 Asian American, Latino, American Indian, and Hawaiian/Pacific Islander tenured and tenure track engineering faculty had minimal growth, and the percentage of African American tenured and tenure track engineering faculty decreased (McGee et al., 2015).

Compensation in engineering. Engineering fields have paid the highest salaries at the start and over the course of one's career relative to other fields. On average, those who hold bachelor's degrees in engineering earn more money than any other major (Carnevale, Cheah, & Hanson, 2015). Within engineering, however, there has been considerable variation in earnings. In 2013, bachelor's degree recipients of petroleum engineering ranked #1 for median annual earnings ($136,000) relative to other majors, whereas civil engineering ranked #12 ($83,00) (Carnevale et al., 2015). Like other disciplines, there have been significant variations in faculty earnings by gender and race/ethnicity within engineering.

Gender and engineering salaries. Academic discipline has been shown to influence salary. Engineering faculty salaries have some of the largest gender gaps in relation to other academic disciplines (Umbach, 2007). In a study of the entire engineering field, Kelly and Grant (2012) found faculty men earned more than faculty women overall. In, science, engineering, and health combined, faculty who identified as men earned higher median salaries than faculty who identified as women in 2013 at the assistant, associate, and full ranks (National Center for Science and Engineering Statistics, 2013). Among engineering faculty at the assistant professor rank when controlling for year since doctorate, median salary for women was higher than men at 4-year institutions with less than 10 faculty but greater for men than women at institutions with greater than 10 faculty (National Center for Science and Engineering Statistics, 2013). (Porter, Toutkoushian, and Moore (2008) found a 3-6% gender pay gap in science and engineering faculty when controlling for institutional type, sector, seniority, and field of instruction; it rose to a 9% gap at research universities. This gender pay gap was not significant within the first three years of hire for assistant professors but emerged over time.

Race/ethnicity and engineering salaries. In a study of science and engineering doctoral degree recipients using longitudinal data from the *Survey of Doctorate Recipients*, racially minoritized women doctoral degree recipients had the lowest gains in salary over the ten-year study period (Webber & Canché, 2015), and the payoff for a doctoral degree was higher for White men than racially minoritized men. Porter, Toutkoushian, and Moore (2008) found between 3-11% unexplained wage gaps for racially marginalized faculty as compared to White faculty in science and engineering for when controlling for institutional type, sector, seniority, and field of instruction. Reviewing science and engineering data from the *Survey of Earned Doctorates*, Gehl (2016) found that in 2013, Black assistant professors had the lowest median salary amount among racial/ethnic groups at $68,000. The median salary of Hispanic and White assistant professors was $70,000 and Asian American assistant professors had the highest median salary at $79,000 at 4-year academic institutions. Gehl (2016) found “when controlling for institutional research intensity, private status, HBCU/Women’s college status, revenue, and reliance on public revenue, the racial pay gap becomes significant” (p. 76). There was a relative gap in the literature on salaries of racially minoritized faculty in engineering as compared to women in engineering.

Summary of the Literature

Administrators and faculty at public universities have faced increasing stakeholder critiques, rising accountability, and declining state financial support. In an era of increasing accountability, resource investments and their outcomes are constantly evaluated, including the investments to expand and diversify students and faculty, especially in the engineering discipline. RCM has become a solid fixture among public institutions of higher education even though positive associations with administrative and learning outcomes have not been established through empirical research. In reference to state budgets, Moody's projected a "'negative' outlook for higher education in 2019, driven by rising costs – primarily labor – that outpace revenue growth" (AASCU Government Relations and Policy Analysis Division, 2019, p. 4). Higher education is labor-intensive, and salaries and wages have comprised a significant (as much as 70%) percentage of a university's budget. Compensation, with the addition of benefits, has traditionally been the largest expense category in higher education (Goldstein, 2012).

Therefore, this study of the relationship between RCM and faculty composition and faculty compensation outcomes broadly and considering gender, gender and race/ethnicity, and the engineering discipline, has filled a gap in existing literature. Distributive justice and procedural justice, tenets of organizational justice theory, offered rationale for studying faculty composition and compensation within the RCM environment and potential inequities from outcomes of RCM implementation at public universities. It has provided administrators with an analysis of some of the potential unintended consequences of RCM implementation. Moreover, it has provided a specific view into a competitive field of national interest with a concerted effort for increasing participation of women-identified and racially minoritized people.

Chapter Three

Methodology

The methodology used to address the research questions is described in this chapter. The selection of the sample, strategies for data collection, and description of variables are included. They are followed by explanations of the difference-in-difference estimation methods, nearest neighbor institutional matching processes, and data analysis procedures used to address the research questions.

The purpose of this study was to examine the relationship between RCM implementation and resource distribution through faculty composition and salaries. I analyzed secondary data primarily drawn from the Integrated Postsecondary Education Data System (IPEDS), the American Society for Engineering Education (ASEE) data system, and publicly available state and institutional websites. The research questions were:

1. What is the relationship between RCM implementation and institutional average salary of assistant professors on the tenure track at public doctoral universities?
    a. when considering gender?
2. What is the relationship between RCM implementation and proportion of assistant professors on the tenure track at public doctoral universities when considering gender?
    a. when considering the intersection of gender and race?
3. What is the relationship between RCM implementation and the proportion of assistant professors of engineering at public doctoral universities when considering gender?
    a. when considering the intersection of gender and race?
4. What is the relationship between RCM implementation and the annual salaries of assistant professors of engineering at two public doctoral universities in Ohio?

Sample Selection

To control for institutional factors, the population for this study was limited to assistant professors on the tenure track from the 195 public, 4-year degree granting doctoral universities in the United States that were eligible for Title IV federal financial aid, based on the 2015 Basic Carnegie Classification in IPEDS contained in the final release data from 2015–2016.

Forty-one institutions from the population were excluded from the study for RQ1 and RQ2 (see Appendix A for excluded institutions and exclusion criteria). Since the purpose of this study was to examine *the effect* of RCM implementation, only those eight institutions that implemented RCM between fiscal years 2012–2017 were selected from the institutions that have implemented RCM to comprise the RCM (treatment) group within the sample. Of these excluded institutions, 26 implemented RCM prior to FY2010, and 6 reported plans to implement RCM (or a hybrid or performance budgeting model) as of fall 2019. Institutions that published plans to implement RCM after FY2021 during this review were not excluded from this study, with the assumption that major changes in advance of the budget model implementation would not be made more than two years before implementation. Other reasons an institution was excluded include lack of publicly available data about an institution's budget model and lack of data available in IPEDS.

Following these exclusions, the sample of universities for an analysis of data available from IPEDS for RQ1 and RQ2 for this study included 154 institutions, eight in the RCM (treatment) group and 146 in the non-RCM (control) group. The treatment group is displayed in Table 3.1, organized by fiscal year of RCM implementation. The control group for RQ1 and RQ2 included the 146 universities within the sample that did not have RCM nor published plans to implement RCM at the time of review. Non-RCM (control group) institutions for RQ1 and RQ2 are listed in Appendix B in alphabetical order.

Table 3.1

Public, Doctoral Research Universities that Implemented RCM 2012-2017

Implementation Year	University Name
2012	Texas Tech University
2013	-
2014	Auburn University Ohio University – Main Campus
2015	University of Virginia – Main Campus
2016	University of Arizona University of California – Davis University of California – Riverside
2017	George Mason University

Note. Year of implementation is reported by fiscal year.

The analysis of ASEE data to address RQ3 used a subset of the sample for RQ1 and RQ2. For RQ3, 37 additional institutions were excluded from the sample used for RQ1 and RQ2 because they did not appear in the ASEE database or were missing necessary data (see Appendix C for institution and exclusion criteria). Therefore, the sample of universities for RQ3 included 117 institutions, eight in the RCM (treatment) group and 109 in the non-RCM (control) group. The RCM treatment group remained the same as displayed in Table 3.1. The institutions in the control group for RQ3 are listed in Appendix D.

To address RQ4, I reviewed available public salary database information for the six states with RCM universities in my sample and online course catalogs for RCM universities. I proceeded with further analysis for Ohio University because I located the Ohio Higher Ed Salary database from the Buckeye Institute that listed annual salary data that was searchable by faculty first and last name, school, department, and year from FY2011 – FY2018. I followed the same nearest neighbor matching process subsequently described, limiting selection to universities in the sample located within the state of Ohio. The first institutional match for Ohio University was the University of Akron, which did not have faculty information available in the course catalog. Therefore, I conducted a second institutional matching process which resulted in the selection of the University of Toledo. I then reviewed the university course catalogs for these institutions to construct a roster of assistant professors of engineering on the tenure track. I excluded any assistant professor that did not appear in both the Ohio salary database and the respective course catalog. This process yielded annual salary information for 135 observations between FY2011 – FY 2017; 75 at Ohio University (RCM/treatment group) and 60 at the University of Toledo (non-RCM/control group). RCM was implemented in FY2014, so I matched institutions based on covariates one year prior to implementation and compared average salary trends three years prior to three years following RCM implementation.

Instrumentation and Variables

The National Study of Postsecondary Faculty was last administered in 2004, leaving a gap in a large-scale, comprehensive data set about higher education faculty and compensation. In the absence of readily available, comprehensive, and longitudinal salary data for individual faculty members grouped by academic disciplines and universities, several data sources were consulted, including the Integrated Postsecondary Education Data System (IPEDS), the American Society for Engineering Education (ASEE) data system, the American Association of

University Professors Collective Bargaining Congress, and publicly available state and university websites.

To explore the relationship between RCM implementation and average weighted monthly faculty salary of tenure track assistant professors (RQ1), I extracted data primarily from IPEDS. The variables chosen from IPEDS to address RQ1 are outlined in Appendix E. The Integrated Postsecondary Education Data System (IPEDS) is a data collection program provided by the Department of Education's National Center for Education Statistics (NCES). All postsecondary education providers submit data about institutional enrollments, completions, costs, and human resources, among others, through online surveys (National Center for Education Statistics, 2015).

To explore the relationship between RCM implementation and proportion of assistant professors of engineering on the tenure track (RQ3), I extracted data from the ASEE database. ASEE provided deans of engineering who contribute to an annual survey and researchers access to the system and published an Engineering College Profiles and Statistics Book, which is shared with engineering deans and posted online. This book included institutional data about engineering enrollments and faculty composition and was available online from 2009–2018. The ASEE database provided the number of assistant professors engineering on the tenure track by biological sex (male or female) and race/ethnicity.

Description of Variables

A description of the variables used in this study is outlined below. Included in this section are the variables used to construct the dependent variables for each research question, independent variable of interest (RCM implementation), and covariates used in nearest neighbor matching process and within difference-in-difference models that incorporated covariates.

Further information on IPEDS variables is included in Appendix E and information on ASEE variables is included in Appendix F.

Institutional average salary of assistant professors on the tenure track. The outcome variable used to address RQ1 was institutional average salary for full-time assistant professors on the tenure track, equated to 9-month contracts in IPEDS. In IPEDS, for FY2017 – FY2019, this variable was defined as "Average salary for instructional staff equated to a 9-month contract-total" and was part of the Human Resources component in the salaries section (Integrated Postsecondary Education Data System, n.d.-c) Average salary was calculated dividing the total salary outlays by the number of instructional staff, which I only captured for the rank of assistant professor on the tenure track. For 2012-16, since "Average salary for instructional staff equated to a 9-month contract" was not available in IPEDS, I took the "Average weighted monthly salary" and multiplied by 9 to create comparable variable for these years and preserved missing values. For 2010-2011, "Average salary of full-time instructional faculty for men and women combined" served as the total average salary dependent variable. More information about the salary definitions from IPEDS is included in Appendix E.

For all salary variables, I created a natural log indexed to FY2019 values using the Higher Education Price Index (HEPI) to address change in dollar values over time and to address skewness and non-normality of distributions as outlined in the tests of normality section of the preliminary data analysis in Chapter 4. For RQ1, the natural log of average institutional salary of assistant professors on the tenure track served as the dependent variable.

Higher Education Price Index. The Higher Education Price Index (HEPI) has been used in prior higher education research on state appropriations (Cheslock, 2006) and instructional expenditures (Romano, 2012; Santos, 2007). HEPI is maintained by the Commonfund Institute:

> HEPI is a more accurate indicator of changes in costs for colleges and universities than the more familiar Consumer Price Index. It measures the average relative level of prices in a fixed basket of goods and services purchased by colleges and universities each year through current fund educational and general expenditures, excluding research. HEPI is compiled from data reported and published by government and economic agencies. The eight categories cover current operational costs of colleges and universities. These include salaries for faculty, administrative employees, clerical employees, and service employees, fringe benefits, utilities, supplies and materials, and miscellaneous services. *(Higher Education Price Index*, n.d.)

For this study, annual salary amounts were indexed to FY2019 using the HEPI, presented in Table 3.2.

Table 3.2

Higher Education Price Index by Fiscal Year

Fiscal Year	HEPI Index
2011	288.4
2012	293.2
2013	297.8
2014	306.7
2015	312.9
2016	317.1
2017	327.8
2018	337.4
2019	345.9

Note. Source: 2019 HEPI Report.

RCM implementation. To collect information on the regressor of interest, RCM implementation, I constructed a binary, independent variable with 0 representing a non-RCM university and 1 representing a university that implemented RCM within the FY2011–FY2017 time period. Universities with an RCM model prior to FY2011 were excluded from analysis because I was interested in the effect of RCM implementation, and I was unable to compare faculty composition and salaries before and after implementation in prior years because of significant missing salary data in IPEDS. Universities with stated plans to implement RCM by FY2019 were excluded from analysis because organizations may begin making changes in anticipation of a new policy, such as a new budget model, and I did not want these potential changes to be accounted for erroneously in the control group. Additionally, we do not have outcome data, such as salary information, available for future years from which to compare. To identify RCM institutions, I consulted prior literature (e.g. (Curry et al., 2013)) and conducted a web search in fall 2019 using RCM and common variants (Responsibility Centered Management, Revenue Center Management, Responsibility Center Budgeting, Incentive Based Budgeting, etc.).

To identify changes in faculty composition and salary by race/ethnicity and gender, I identified several variables in IPEDS from which to construct institutional average salary by gender (RQ1a), proportions of assistant professors by gender (RQ2), and proportions of assistant professors by gender and race/ethnicity (RQ2a) in IPEDS.

Gender. Gender was reported in IPEDS using a dichotomous, categorical variable, man or woman. Although this variable was not representative of the total spectrum of gender identity expressions, it was how the data set in IPEDS was structured and available to address my research questions. For RQ1a, the natural log of average institutional salary of assistant professors on the tenure track for men served as the first dependent variable and the natural log of average institutional salary of assistant professors on the tenure track for women served as the second dependent variable for a second difference-in-difference estimation. For RQ2, I generated a new variable for each institution that took the number of men assistant professors and divided that by the total number of assistant professors. I created an institutional proportion for women assistant professors using the same procedure. These gender proportions each served as the dependent variables for RQ2 for two difference-in-difference estimations.

Race/ethnicity. The race/ethnicity categories available in IPEDS were American Indian or Alaska Native, Asian, Black or African American, Hispanic or Latino, Native Hawaiian or Other Pacific Islander, Nonresident Alien, Race/Ethnicity Unknown, Two or More Races, or White. Although this variable was not representative of the total spectrum of race/ethnicity identity expressions, it was how the data set in IPEDS was structured and available to address my research questions. See Appendix E for a description of the race/ethnicity categories extracted from IPEDS.

I downloaded the total number of assistant professors on the tenure track at each institution in my sample in each race/ethnicity category for men and then for women. For RQ2a, I generated a new variable for each institution that took the number of men assistant professors in each race/ethnicity category and divided that by the total number of assistant professors. I then created an institutional proportion for women assistant professors from each race/ethnicity category using the same procedure. These gender and race/ethnicity proportions each served as a dependent variable for unique difference-in-difference estimations for RQ2a.

Several institutional predictors of faculty compensation and composition were included in this analysis as covariates, including Basic Carnegie Classification, collective bargaining/union control, fall graduate and undergraduate student enrollment, and degree of urbanization.

Carnegie Classification. Based on the 2015 Carnegie Basic classifications, doctoral institutions are divided into Highest Research Activity, Higher Research Activity, and Moderate Research Activity. Carnegie Classification was examined through the institutional matching process as well as an explanatory variable for difference-in-difference estimations with covariates. A more detailed variable description is located in Appendix E. Of the 195 universities in the population, 81 were classified as doctoral universities with highest research activity, 75 with higher research activity, and 39 with moderate research activity.

Degree of urbanization (urban-centric locale). Locale codes identify the geographic status of a school on an urban continuum ranged from "large city" to "rural" and were based on a university's physical address. This variable was included as a proxy for an area's cost of living. Further description of the variable is in Appendix E.

Fall student enrollment. I used the fall enrollment (undergraduate) and fall enrollment (graduate) variables as part of the institutional matching process and in the difference-in-difference estimation models with covariates. The definitions for these variables are presented in Appendix E. These variables were chosen as one way to control for the impact of institutional size on raw numbers of assistant professors.

To address RQ3, (*proportion of assistant professors of engineering when considering gender*), I extracted the variables listed in Appendix F from the American Society for Engineering Education (ASEE) Data Management System. To identify changes in faculty composition and salary by race/ethnicity and gender, I identified several variables to construct institutional proportions of engineering assistant professors by gender (RQ3) and gender and race/ethnicity (RQ3a) in the ASEE database. I created proportions of assistant professors of engineering on the tenure track by dividing the total number of assistant professors of engineering on the tenure track by the numbers of assistant professors of engineering on the tenure track for each respective gender (RQ3) and gender and race/ethnicity grouping.

Gender. Biological sex was reported in ASEE using a dichotomous, categorical variable, male or female. I recoded male and female to man and woman to serve as a proxy for gender.

Although this variable was not representative of the total spectrum of gender identity expressions, it was how the data set in ASEE was structured and available to address RQ3.

Race/ethnicity. ASEE race/ethnicity categories were: Black or African American, Asian American, Hispanic or Latino, Native American, Native Hawaiian or Other Pacific Islander, Caucasian or White, Race/Ethnicity: Other, Race/Ethnicity: Unknown, or Two or More Races. See Appendix F for a thorough description of the race/ethnicity categories extracted from ASEE used for RQ3a of this study. Although this variable was not representative of the total spectrum of identity expressions for race and ethnicity, it was how the data set in ASEE was structured and available to address RQ3.

To address RQ4, (*annual salaries of assistant professors of engineering at two public doctoral universities in Ohio*) I used variables of faculty name, school (Ohio University, University of Toledo), department, job description (rank and track), earnings (annual salary gross wages), and year from the Higher Ed Salary database provided by the Buckeye Institute. I used variables of faculty name, rank, and college/department from the Ohio University and University of Toledo course catalogs.

Unionization. Data for unionization was gathered from the website of the American Association of University Professors (AAUP) Collective Bargaining Congress. The AAUP Collective Bargaining Congress is the overarching organization for more than 80 unionized AAUP chapters. The majority of chapters represent faculty at public institutions, although private institutions are also represented. Unionization was operationalized as the presence of a collective bargaining agreement from the list of AAUP Collective Bargaining Congress chapters. A nominal dichotomous categorical variable was dummy coded as (0=Not Unionized, 1=Unionized) to represent the presence of a collective bargaining agreement. This variable was not used as a covariate for the first three research questions because there were no universities with collective bargaining chapters in the RCM group. I did include unionization as a covariate for RQ4 because the University of Toledo had a collective bargaining chapter. The presence of a union at a university has been shown to influence faculty salaries (Clery, 2015; Ogun, 2016), although in a comparison of teaching faculty salaries in 2013-2014 in IPEDS, Clery (2015) found unionization to impact faculty salaries, but not within the engineering discipline.

Method

This quantitative study used Ordinary Least Squares (OLS) regression to estimate a difference-in-difference model for panel data with salary and proportions of assistant professors on the tenure track. I used this method to compare outcomes at institutions that implemented RCM (treatment group) to institutions that did not (control group) to determine if the change and direction in the outcomes were difference from at RCM institutions than institutions with other budget models. Difference-in-difference estimation offers several advantages, such as the ability to easily add additional institutions, covariates, and time periods to the regression equation (Angrist & Pischke, 2009). In a review of 92 difference-in-difference empirical journal articles, Bertrand et al. (2004) found employment (18 studies) and wages (13 studies) to be the most used dependent variables. Bertrand et al. (2004) offered evidence for the appropriateness of difference-in-difference as a method for this study, and Card (1992) offered a precedent for using averages in difference-in-difference estimations. Frey (2012) provided a precedent for using eight treated units (states) in a difference-in-difference estimation model.

Difference-in-Difference Estimation

Difference-in-difference estimation is often used to analyze policy implementation (Bailey, 2016) to determine if the policy change of interest (i.e. RCM budget model implementation) was "the only source of variation between the treatment and control groups" (Delaney & Kearney, 2015). Policies may be studied by categorical, dummy variables, or by continuous variables (Angrist & Pischke, 2009). The implementation of a new RCM budget model was analogous to the implementation of a new institutional policy and was operationalized as the independent variable of interest for this study as a dichotomous, categorical dummy variable (0=no RCM implementation or not treated, 1=RCM implementation or treated).

Difference-in-difference estimation calculates two differences, the first for the difference between the pre- and post-tests of the dependent variable for each of the respective treatment and control groups and then compares the difference between these scores (Angrist & Pischke, 2009) to enable causal inferences (Delaney & Kearney, 2015). Difference-in-difference analysis uses aggregate "data with a time or cohort dimension to control for unobserved but fixed omitted variables" (Angrist & Pischke, 2009, p. 221). This study used descriptive and inferential statistics. The software package Stata15 was used to implement various panel data versions of a difference-in-difference estimation model after I conducted an institutional, nearest neighbor matching process.

Institutional Matching Process

Following the procedures of Dettmann, Giebler, and Weyh (2019), I used the flexpanelid command to match institutions based on similar characteristics one year prior to treatment and observe average salaries of assistant professors from year of RCM implementation to two years following RCM implementation. Before downloading flexpaneldid, I installed the Stata ado-files psmatch2, pstest and cem, which are used by flexpaneldid. I used the Stata command to explore research questions one through three:

flexpaneldid [dependent variable], id(unitid) treatment(rcm) time(year) statmatching(con(grad ug)cat (carnegie urban)) outcometimerelstart(2) matchtimerel (-1) outcomedev(-1) test

The flexpaneldid command required the individual identification of the institutions (*unitid*), the dichotomous treatment variable (*rcm*), and the variable identifying the time of the matched sample, or one year prior to RCM implementation, in the panel data (*year*).

The treatment effect was estimated according to the nearest neighbor statistical distance matching approach described above (statmatching). Institutions were matched using a combination of the means of the continuous variables (con) of fall undergraduate student enrollment (ug) and fall graduate student enrollment (grad), as well as the categorical variables (cat) of Carnegie Classification (carnegie) and Degree of Urbanization (urban). Fall enrollment for undergraduate and graduate students were included as a matching covariate because Rabovsky and Lee (2018) found total enrollment to be negatively associated with the gender pay gap and Lee and Won (2014) found the gender pay gap to increase at larger research universities. Faculty salaries have differed based on institutional type (Luna, 2007; Renzulli et al., 2013), with doctoral institutions having gender salary gaps (American Association of University Professors, 2018; Meyers, 2011). The Carnegie Basic Classifications were chosen as a matching covariate to differentiate between level of research activity at doctoral universities.

The pre-treatment outcome was defined by the treatment start for matching (matchtimerel (-1), or one year prior to rcm implementation): outcomedev(-1) in relation to the treatment start. The matching time is defined by matchtimerel(-1), or one year prior to RCM implementation for each treated institution. The end point of the observed outcome is related to the treatment start (RCM implementation) through two years following RCM implementation, indicated by outcometimerelstart(2). The command (test) indicates the statistical tests that will be used to test the success of the statistical matching procedure and its results.

Preprocessing then occurred to organize the data by treated units and treatment times. Then the matching procedure identified the nearest statistical neighbor to pair treated (RCM) institution(s) with non-treated (non-RCM) institution(s). The statamatching procedure was executed using the means of the continuous variables grad and ug, fall enrollment for graduate students and undergraduate students respectively, and categorical variables for Basic Carnegie Classification (carnegie) and degree of urbanization (urban) to match similar institutions based on treatment status (RCM) at one year prior to RCM implementation.

Evaluation of Matched Samples

Next, I evaluated the similarity of the matched groups using the Stata command pstest by Leuven and Sianesi (2003), which displays the balance of variable distributions in the treatment (RCM) and control (non-RCM) group before and after matching. Dettmann, Becker, and Schmeiber (2011) offer evidence that statistical matching is better than propensity score matching for small sample sizes. Following the illustration outlined by (Dettmann et al., 2019), I evaluated the similarity of the RCM and non-RCM matched pairs by examining the means and variances, Rubin's test, a visual examination of quantile plots, two-sample Kolmogorov-Smirnov test for equality of distribution functions, and chi-square tests for each matched sample for each difference-in-difference estimation. The tests were conducted for the time of matching, or one year before the implementation of RCM, so each of the variables have *_pre1* appended to the variable name to reflect the matching year.

The means serve as "a measure for the standardized percentage difference – or bias – between the means in both groups" (Dettmann et al., 2019, p. 14). If the p-value is less than 0.05, than I concluded that the means for the treated and non-treated groups were not balanced. The variance ratio is the variance of the treatment group divided by the variance of the control group (Dettmann et al., 2019). A variance ratio of 1 is considered perfectly balanced, but an "asterisk is displayed for variables that have variance ratios that exceed the 2.5th and 97.5th percentiles of the F-distribution with (number of [matched] treated minus 1) and (number of [matched] treated minus 1) degrees of freedom (Leuven & Sianesi, 2003). If the variance ratio for any matching variable fell outside this range, there was evidence that the variable was not balanced.

I then applied Rubin's test to the treated and non-treated groups. Rubin's B identifies the "number of standard deviations between the means" of the treated and non-treated group (Rubin, 2001, p. 175). If Rubin's B was greater than 25%, this provided evidence that the groups were not balanced (Dettmann, et al., 2019). Rubin's R is "the ratio of treatment variance to control variance" (Rubin, 2001, p. 175). If Rubin's R fell outside the 0.5-2 range, this provided evidence that the treated and non-treated groups were not balanced (Dettmann, et al., 2019). The pstest command placed an asterisk by values that did not meet Rubin's (2001) recommendations for balanced samples (Leuven & Sianesi, 2003).

I then visually inspected the quantile-quantile plots for the covariates for each match. These plots graphed "the extent of covariate imbalance in terms of standardized percentage differences using dot charts" (Leuven & Sianesi, 2003). If all dots in a plot fell on the 45-degree line, the distributions for that variable for the two groups were identical. Caution was used for interpreting visual plots for categorical variables, as the plots only offered "rough guides for similarity" (Dettmann, et al., 2019, p. 11).

The results of the two-sample Kolmogorov-Smirnov test for equality of distribution functions verified the matching procedure used based on statistical distance for continuous variables. In the Kolmogorov-Smirnov test, a corrected p-value for a covariate that was less than 0.05 indicated that the distributions for that variable for the treated group and the control group were statistically significantly different (Dettmann, et al., 2019).

The results of the chi-square test verified the matching procedure based on statistical distance for categorical variables. In the Chi-square test, a p-value for a covariate that was less than 0.05 indicated that the distributions for that variable for the treated group and the control group were statistically significantly different (Dettmann, et al., 2019).

I used the same matching and evaluation of matched samples process for research questions one through three. For RQ4, I used the matching process to identify an appropriate institutional pair for Ohio University, a university in the treatment group that implemented RCM in FY2014. The first match was the University of Akron, but faculty were not listed in the institution's course catalog and no departmental data existed in the Ohio salary database for 2016 and 2017, so I was unable to construct an accurate roster of engineering assistant professors. Therefore, I conducted the analysis for RQ4 with the second best institutional match, the University of Toledo. The universities shared the same Carnegie Classification and region but differed by urbanization. The Kolmogorov-Smirnov evaluation of matched pairs tests indicated no significant differences in the distributions for fall graduate enrollment and fall undergraduate enrollment for Ohio University and the University of Toledo at the time of matching, one year prior to RCM implementation.

Flexible, Conditional Difference-in-Difference Model

To address RQ1-RQ3, I used a novel, time variant difference-in-difference estimation procedure outlined by Dettman, et al. (2019), which is applicable for "economics of education and labor market research" (p. 1). I used this procedure, rather than a standard difference-in-difference estimation to allow for the varying fiscal years of RCM implementation by treatment universities within the sample. For this procedure, "the compared outcome changes are defined conditional on matched samples instead of the whole samples of treated and non-treated" institutions (Dettman, et al., 2019, p. 3). This equation described an ordinary least squares (OLS) bivariate regression with RCM implementation as the independent variable of interest. Dettman, et al. (2019) provided the equation on which this difference-in-difference estimation with time variant treatment is predicated (p. 7):

$$ATT = \frac{1}{I}\sum_{i=1}^{I}(Y_{i,t_{0i}+\beta_i} - Y_{i,t_{0i}}) - (Y_{j,t_{0i}+\beta_i} - Y_{j,t_{0i}})$$

Where

ATT = average treatment effect for the treated
Y = outcome
i = treated institutions
j = institutional controls
t_{0i} = individual start time of treatment (year of institution RCM implementation)
$t_{0i} + \beta_i$ = individual duration from year of RCM implementation to end of observation (two years after RCM implementation)

After the results of the flexible, conditional, difference-in-difference model were displayed, I reviewed the results of two fixed effects difference-in-difference models contained within the flexpaneldid command. These models included a mean fixed effects difference-in-difference estimation and a dynamic fixed effects difference-in-difference estimation. I then conducted another difference-in-difference estimation that added covariates.

Fixed Effects Difference-in-Difference Models

Adding fixed effects to the regression models offered the advantage of addressing endogeneity. Endogeneity is another challenge in quasi-experimental studies and occurs if changes in an independent variable "are related to other factors that influence the dependent variable" (Bailey, 2016, p. 8). To address endogeneity, I ran additional difference-in-difference estimations that incorporated fixed effects that "capture differences in the dependent variable associated with each unit" (Bailey, 2016, p. 253). I removed these fixed effects (i.e., geographical or institutional factors) from the error term to address endogeneity and remove "a source for the correlation of the error term and an independent variable" (Bailey, 2016, p. 254).

Mean fixed effects difference-in-difference estimation. To estimate the treatment effect, I used the constant and time (year) dummy variables for the 2-year outcome development period, from RCM implementation through two years following implementation in the flexpaneldid command. No additional covariates were included in this model.

Dynamic fixed effects difference-in-difference estimation. This model was similar to the mean fixed effects difference-in-difference model. I used the constant and time (year) dummy variables for the 2-year outcome development period, from RCM implementation through two years following implementation in the flexpaneldid command. However, in this model, the time (year) dummy variable coding scheme to estimated the treatment effect, not just for the entire 2-year period following RCM implementation, but also effects for start through year one and from year one to year two. No additional covariates were included in this model.

Fixed effects difference-in-difference estimation with covariates. After the institutional matching procedure in the flexpaneldid command, a new dataset was generated containing only the universities matched, covariates used in the matching procedure, and variables for the start of treatment, treatment outcome, and interaction of treatment and post-treatment. I was then able to regress RCM implementation on the matched sample with the addition of the covariates used in the matching process (fall undergraduate enrollment, fall graduate enrollment, urbanization, and Carnegie classification) in a fixed effects regression model.

Standard Difference-in-Difference Estimation

To address RQ4, I was able to use the standard difference-in-difference model because there was only one time of treatment, FY2014, when Ohio University implemented RCM. Bailey (2016) provided a general OLS model to estimate difference-in-difference using a dichotomous variable to demonstrate treatment and control groups while incorporating time:

$$Y_{it} = \beta_0 + \beta_1 Treated_i + \beta_2 After_t + \beta_3 (Treated_i \times After_t) \beta_4 X_4 + \varepsilon_{it}$$

Where

Y = logged individual annual salary of assistant professors of engineering on the tenure track for institution i in year t
β_0 = mean for control group
β_1 = difference across salaries before and after treatment
β_2 = difference that exists across all salaries for each time period
Treated$_i$ = 0 for control institution (University of Toledo), 1 for treated institution (Ohio University)
After$_t$ = 1 for all units from treatment and control group
β_3 = coefficient of interest on the interaction between Treated$_i$ and After$_t$
$\beta_4 X_4$ = covariate
i = university
t = fiscal year
ϵ = error term

As decision-makers often adjust budgets in anticipation of forthcoming policy changes (Angrist & Pischke, 2009), the adoption (fiscal) year of RCM represents year 1 of the policy, or t=1. The error term is "associated with unmeasured factors in a regression model" (Bailey, 2016, p. 5). The OLS model permitted the addition of covariates to the equation above and produced standard errors on the estimate.

I followed the procedure as described by (Hillman, 2018) to conduct a difference-in-difference estimation comparing the annual salaries of assistant professors of engineering at Ohio University and the University of Toledo from FY2011 – FY 2017 (three years prior and following) RCM implementation at Ohio University in FY 2014. I assigned Ohio University to the “treat” group and generated a “post” variable where years prior to RCM implementation (before 2014) were named “pre” and years equal to or greater than FY 2014 were named “post”.

Methodological Limitations

Like all research, this study had several methodological limitations. I used observational data from existing, secondary data sources. Multiple data sources were consulted because engineering assistant professor salary data and faculty demographics are not available in a single, national data source. Although IPEDS is one of the most comprehensive data sets available for higher education in the United States, with mandatory participation and a nearly 100% response rate, a comprehensive study of the reliability and validity of IPEDS data, including a review of salaries, employees by position, and enrollment, from which much of the data for this study was drawn has not been conducted since a review of data submitted in 2003-2004 (Jackson et al., 2005). IPEDS data lacked the ability to track faculty salary, discipline, or demographics at the individual level, and ASEE did not offer salary data nor measures of reliability or validity. Therefore, human error may have occurred when collecting data from and comparing multiple data sources.

There may be other factors outside the scope of this study that influence the results. Omitted variable bias, one limitation for policy treatment effect studies, may be reduced by adding robust control variables to the analysis (Cellini, 2008; Li, 2016; Sherman, 2003). Several covariates were used in the nearest-neighbor matching process (Carnegie Classification, region, urbanization, fall undergraduate student enrollment, and fall graduate student enrollment). A fourth difference-in-difference model was also examined with these variables as covariates.

Unionization was added as a sixth covariate for the difference-in-difference estimation with covariates in RQ4 to reduce these concerns.

In order to meet the standard for causal inference, difference-in-difference estimations must meet the parallel trends assumption. The "potential outcome is derived from the parallel trends that we assume exists between the treated and comparison groups" (Furquim, Corral, & Hillman, 2020, p. 8). In other words, if the treatment was never applied to the treatment group, its trend would equal the trend of the control group (Furquim et al., 2020). There is no statistical formula to test this assumption, but rather it is a visual inspection of the trends of the treatment and control group prior to and following treatment.

Although difference-in-difference is a widely accepted method to measure policy impact, Jaquette et al. (2018) argued "difference-in-difference is inappropriate for analyses of RCM because this strategy estimates average treatment effects across universities, but RCM policies differ dramatically across universities. Thus, difference-in-difference estimates of the effect of RCM are likely biased toward zero because the estimates are an average of the effect of effective RCM models and the effect of ineffective RCM models" (p. 13). The regressor of interest, RCM implementation, "varies only at a more aggregate or group level," in this case the institution (Angrist & Pischke, 2009, p. 227).

To address the concern described by Jaquette et al. (2018), I reviewed the websites of the institutions in the treatment (RCM) group to identify the revenue and expense allocations associated with each RCM model. Each RCM university had a unique budget model that allocated expenses differently based on formulas or flat rates, often based on a combination of student and/or employee FTE or headcounts. Facilities costs were often based on square footage of space. Most universities had a centralized fund for strategic planning. For example, the

"Mission Enhancement Fund" at Auburn University taxed revenue (not including investment, gift, and sponsored research revenue) at a rate of 17.5% (See Appendix G). A comparison of tuition and sponsored activity revenue allocations is presented in Appendix G. As the table demonstrated, most RCM universities allocated undergraduate tuition (net financial aid and the subvention fund) based on formulas of 60-85% going to the college of instruction based on student credit hours and 15-30% going to the college of major. Two universities within the same system also allocated a percentage to college based on degree completion. Most of the RCM universities in the sample allocated graduate tuition (less aid) solely to college of major.

Sample size. Since I was interested in the effects of RCM implementation on faculty composition and compensation, I limited the time period of the sample to coincide with outcome variables of interest reported to IPEDS for institutional average salary of faculty and numbers of faculty. Salary data was not required in FY2010, which resulted in significant missing data. Therefore, in order to permit a year prior to RCM implementation for the outlined matching process and two years within which to observe the effects of policy changes, I limited the time period of RCM implementation to FY2012 – FY 2017, which decreased the number of RCM institutions in my sample to eight. If I had an increase in sample size by adding more institutions, I might be more likely to get a significant result. However, by increasing the time period, I might also see more confounding factors as hiring patterns have shifted over the past decade. Difference-in-difference has been used in higher education applications with small sample sizes. Hillman (2018) provided an illustrative example of a difference-in-difference application with eight treatment and eight control institutions for an n=16. In a study of merit-based aid, Frey (2012) had eight states in the treatment group, and in their review of difference-in-difference literature, Bertrand et al. (2004) confirmed that many researchers conduct difference-in-difference studies with less than 50 states (or units) in the sample to "focus only on comparable controls" (p. 261).

My exploratory analysis of salaries of assistant professors of engineering at two institutions in Ohio also suffered from limitations due to sample size. My sample size decreased readily by retaining assistant professors that appeared in both the compensation data and the faculty catalog. To further increase sample size of faculty, I would also rely more heavily on the compensation websites and not cross check faculty rosters with course catalogs, for which data entry deadlines for publication may not align with fiscal year salary reporting. Another option for future research would be to keep the use of university catalogs as a strategy to control for promotions on the tenure track, to account for the temporary decrease in salary among assistant professors in the department.

Missing values. As with most datasets involving survey responses or observation of existing data, there were several instances of missing values in these datasets. Three institutions were excluded from the study because of large amounts of missing data and one institution was excluded from the study due to missing faculty salary information for a year of the study in IPEDS as described in Appendix A. Twenty-two additional institutions were excluded from the study for RQ3 that did not appear in the ASEE database and 14 institutions were excluded for missing faculty counts during the study period, as outlined in Appendix C. Since I chose to use Stata to analyze the data, the remaining missing values were handled through listwise deletion, which "discards observations with missing values on one or more variables of interest" (Cheema, 2014, p. 493). Missing values for variables of interest were provided in the descriptive statistics in Chapter 4.

Assumption testing. This study did not benefit from random assignment for policy (RCM) implementation, the independent variable of interest. However, difference-in-difference estimation enables the estimation of causal relationships (Angrist & Pischke, 2009; Bertrand et al., 2004) if assumptions are met. To reduce the risk of confounding variables and demonstrate that the regressor of interest (RCM) was the only variable responsible for the variation between the control and treatment groups, I added covariates to difference-in-difference estimation models. I also reviewed the covariate distributions to test for equality of matched samples and I reviewed the parallel trend assumption for RQ4.

Chapter Four

Results

The results of difference-in-difference analyses comparing the relationship between RCM implementation, composition, and compensation of assistant professors are presented in this chapter. Preliminary data analysis using descriptive statistics are first presented and organized into three sections by data source: 1) IPEDS, 2) ASEE, 3) Ohio. Within these sections the descriptive statistics are organized by research question. Then the results of institutional nearest neighbor matching processes and difference-in-difference estimations are presented, again organized by data source and research question.

Descriptive Statistics for IPEDS Analyses

The descriptive statistics for the key salary variables for RQ1 (*institutional average salary of assistant professors on the tenure track*) and RQ1a (*gender consideration*) are provided in Tables 4.1 - 4.7. Descriptions of variables extracted from IPEDS for this study are listed in Appendix E. Descriptive statistics for the annual institutional average salary of assistant professors on the tenure track (*salary*) by RCM implementation are summarized in Table 4.1. For FY2019, the mean salary for assistant professors was $77,880 at non-RCM institutions and $85,141 at RCM institutions.

Table 4.1

Descriptive Statistics for Average Salary by RCM Implementation

Variable	*n*	*M*	*SD*	Minimum	Maximum
Non-RCM Institutions					
salary2011	154	66508	8003	49588	92433
salary2012	153	67702	8420	51254	101044
salary2013	153	67865	8903	44460	98388
salary2014	151	69487	9108	48222	100611

salary2015	150	71181	9905	47817	104994
salary2016	147	72670	10380	50751	110916
salary2017	146	74837	10923	52465	111489
salary2018	146	76500	11530	53232	111703
salary2019	146	77880	12343	53538	118176
RCM Institutions					
salary2012	1	65923	-	65923	65923
salary2013	1	68796	-	68796	68796
salary2014	3	66828	3495	62793	68886
salary2015	4	73341	9985	65358	87930
salary2016	7	79110	9099	68787	92043
salary2017	8	80913	8413	72811	93839
salary2018	8	82072	7389	74365	93768
salary2019	8	85141	8145	77260	98988

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for salary2012 and salary2013 because *n*=1. The number of RCM institutions (*n*) is a cumulative count (for example, there were a total of 8 universities that had implemented RCM by FY2017 in my sample. Although other institutions implemented RCM in FY2018, they are not included here because they are not in my sample of institutions that implemented RCM between FY2012 – FY2017.

Descriptive statistics for the annual institutional average salary of men who are assistant professors on the tenure track (*salarym*) by RCM implementation are summarized in Table 4.2. Average salaries for men at RCM institutions appear to be higher than for men at non-RCM institutions but with less variation in the smaller treatment group. Men at non-RCM institutions had a mean salary of $80,720 in FY2019, whereas men at RCM institutions had a mean salary of $89,228.

Table 4.2

Descriptive Statistics for Average Salary for Men by RCM Implementation

Variable	*n*	*M*	*SD*	Minimum	Maximum
Non-RCM Institutions					
salarym2011	154	68326	8403	51553	92533
salarym2012	153	69735	8769	51553	102366
salarym2013	153	70027	9223	45567	97884
salarym2014	151	71695	9498	46647	102528
salarym2015	150	73648	10552	48474	107955
salarym2016	147	75195	10920	49554	113607
salarym2017	146	77623	11533	50342	114658
salarym2018	146	79417	12136	51839	116499
salarym2019	146	80720	13146	51079	122484
RCM Institutions					
salarym2012	1	68094	-	68094	68094
salarym2013	1	71262	-	71262	71262
salarym2014	3	69897	5039	64080	72936
salarym2015	4	76964	9692	67833	90639
salarym2016	7	82369	9022	70740	96435
salarym2017	8	85018	8258	76033	98838
salarym2018	8	86139	7997	75901	95620
salarym2019	8	89228	8182	79194	99710

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for salary2012 and salary2013 because *n*=1.

Descriptive statistics for the annual institutional average salary of women assistant professors on the tenure track (*salaryw*) by RCM implementation are summarized in Table 4.3. Average salary for women at RCM institutions was higher than at non-RCM institutions but had less variation with a smaller number of institutions. Women assistant professors at non-RCM institutions had a mean salary of $74,877 in FY2019, whereas women at RCM institutions had a mean salary of $80,604.

Table 4.3

Descriptive Statistics for Average Salary for Women by RCM Implementation

Variable	*n*	*M*	*SD*	Minimum	Maximum
Non-RCM Institutions					
salaryw2011	154	64500	7804	47729	92929
salaryw2012	153	65498	8269	49805	98971
salaryw2013	153	65523	8600	43560	99225
salaryw2014	151	67098	8763	47961	99054
salaryw2015	150	68525	9360	46890	104445
salaryw2016	147	69961	9731	48699	103887
salaryw2017	146	71775	10254	50786	102248
salaryw2018	146	73350	10960	49882	107282
salaryw2019	146	74877	11579	53636	112962
RCM Institutions					
salaryw2012	1	62170	-	62170	62170
salaryw2013	1	65187	-	65187	65187
salaryw2014	3	62931	1971	61038	64971
salaryw2015	4	69174	10740	62055	85140
salaryw2016	7	75470	9401	66150	86985
salaryw2017	8	76358	8726	68431	88737
salaryw2018	8	77737	7297	70545	91582
salaryw2019	8	80604	8668	72817	98034

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for salary2012 and salary2013 because *n*=1.

The results of tests of normality for institutional average salary (salary), average salary for men (salarym), and average salary for women (salaryw) assistant professors on the tenure track are presented in Table 4.4. Based on p-values of less than 0.05 for Skewness, I rejected the hypothesis that the salary distribution was normal for fiscal years (all except 2011 and 2013). I rejected the hypothesis that salary for men assistant professors had a normal distribution for three years (2012, 2014, 2016) with $p<0.05$ each, and I rejected the hypothesis that the salary distribution for women assistant professors from FY2011 – FY 2019 was normal, with $p<0.05$.

Based on the p-values for Kurtosis, I was unable to reject the hypotheses that distributions for average salary of assistant professors (except 2012), average salary of men assistant professors, and average salary of women assistant professors (except 2011-2013) were normal. Based on the combined adjusted Chi-square test, I rejected the hypothesis that the distribution was normal for average salary and average salary for men for 2012, 2014, and 2016 with $p<0.05$. Based on the combined adjusted Chi-square test, I rejected that the hypothesis that the distribution was normal for average salary for women for all years except 2017 with $p<0.05$.

Table 4.4

Tests for Normality for Salary of Assistant Professors by Gender and RCM

Variable	*n*	Skewness (*p*)	Kurtosis (*p*)	Adjusted X^2	*p*
salary2011	117	0.063	0.397	4.240	0.120
salary2012	117	0.002*	0.028*	11.940	0.003*
salary2013	117	0.098	0.186	4.560	0.102
salary2014	117	0.017*	0.163	7.110	0.029*
salary2015	117	0.046*	0.216	5.440	0.066
salary2016	117	0.010*	0.080	8.680	0.013*
salary2017	117	0.032*	0.369	5.360	0.069
salary2018	117	0.019*	0.505	5.750	0.057
salary2019	110	0.020*	0.454	5.810	0.055
salarym2011	117	0.139	0.859	2.250	0.324
salarym2012	117	0.009*	0.117	8.450	0.015*
salarym2013	117	0.208	0.400	2.330	0.312
salarym2014	117	0.030*	0.169	6.310	0.043*
salarym2015	117	0.174	0.251	3.220	0.200
salarym2016	117	0.029*	0.070	7.420	0.025*
salarym2017	117	0.081	0.299	4.200	0.123
salarym2018	117	0.070	0.621	3.580	0.167

salarym2019	110	0.106	0.463	3.200	0.202
salaryw2011	117	0.007*	0.025*	10.650	0.005*
salaryw2012	117	0.000*	0.002*	19.690	0.000*
salaryw2013	117	0.023*	0.047*	8.230	0.016*
salaryw2014	117	0.013*	0.167	7.460	0.024*
salaryw2015	117	0.012*	0.130	7.900	0.019*
salaryw2016	117	0.014*	0.459	6.250	0.044*
salaryw2017	117	0.046*	0.867	4.090	0.130
salaryw2018	117	0.011*	0.508	6.600	0.037*
salaryw2019	110	0.004*	0.406	8.140	0.017*

Note. Significant at $*p<0.05$. P-values are displayed in Skewness and Kurtosis columns. $n=154$.

Since the distribution for all three salary variables was skewed, I created new salary variables using the natural log with a base of 10. Furthermore, to control for changes over time, I indexed each salary variable prior to FY2019 to the FY2019 salary amounts based on the Higher Education Price Index (HEPI). I named the logged, indexed variable for salary *nsalary*, the dependent variable for RQ1. I named the logged, indexed variables for salary of men assistant professors *nsalarym* and salary of women assistant professors *nsalaryw,* the dependent variables for RQ1a.

Two fixed variables served as covariates in this study, region and unionization. The Bureau of Economic Analysis (BEA) regions in IPEDS served as a covariate for each research question in this study. These regions group states by similar economic and labor force characteristics and are a fixed variable for the period of record of this study. Eight of the regional classifications included institutions in this sample (New England, Mid East, Great Lakes, Plains, Southeast, Southwest, Rocky Mountains, and Far West); two regional classifications were not represented in the sample (U.S. Service Schools and Outlying Areas). The number and percentage of institutions in the study sample in the eight regions are displayed in Table 4.5.

Table 4.5

Number and Percentage of Institutions in Each Region by RCM

	Non-RCM		RCM	
Region	*n*	%	*n*	%
Southeast	44	30	3	38
Southwest	20	14	2	25
Great Lakes	19	13	1	13
Far West	17	12	2	25
Mid East	15	10	-	-
Plains	13	9	-	-
Rocky Mtns	10	7	-	-
New England	8	5	-	-
Total	146	100	8	100

Note. Data from FY2017 are displayed following RCM implementation within sample. *n*=154. Percentages are rounded to the nearest whole number.

The number and percentage of institutions with unionization are shown in Table 4.6. The description for unionization may be found in Chapter 3. This covariate was fixed for this study and based on data collected in fall 2019 from the American Association of University Professors Collective Bargaining Congress. There were no unionized institutions that implemented RCM in the sample during the period of record.

Table 4.6

Number and Percentage of Institutions with Union Chapters

	Non-RCM		RCM	
Unionization	*n*	%	*n*	%
No union	128	88	8	100
Union	18	12	-	-
Total	154	100	8	100

Note. Data from FY2017 are displayed following RCM implementation within sample. *n*=154. Percentages are rounded to the nearest whole number.

The descriptive statistics for additional key variables to examine RQ2 (*proportion of assistant professors on the tenure track by gender*) and RQ2a (*intersection of gender and race/ethnicity*) are presented in Tables 4.7 - 4.16. Raw numbers are presented for the ease of the reader for descriptive statistics for assistant professors by gender and race/ethnicity, but proportions of assistant professors by gender and race/ethnicity are used for difference-in-difference estimations to control for differences in institutional sizes. Numbers of assistant professors had higher proportions of missing values for FY2011, FY2013, and FY2015 in IPEDS because of optional reporting for those years.

Table 4.7

Descriptive Statistics for Assistant Professors by Gender and RCM

	Missing		Non-RCM Institutions			RCM Institutions		
Variable	*n*	%	*n*	*M*	*SD*	*n*	*M*	*SD*
rtotal2011	22	14	132	187.985	107.990	-	-	-
rtotal2012	-	-	153	177.020	100.565	1	255.000	-
rtotal2013	19	12	134	174.127	102.835	1	246.000	-
rtotal2014	-	-	151	170.834	101.170	3	243.667	41.861
rtotal2015	14	9	136	177.154	107.029	4	229.500	48.363
rtotal2016	-	-	147	178.857	112.173	7	202.286	58.349
rtotal2017	-	-	146	185.849	111.503	8	259.750	164.143
rtotal2018	-	-	146	188.349	114.723	8	219.625	71.887
rtotal2019	-	-	146	190.589	119.953	8	267.750	163.532
rmen2011	22	14	132	104.402	63.103	-	-	-
rmen2012	-	-	153	96.941	57.647	1	132.000	-
rmen2013	19	12	134	94.485	57.335	1	113.000	-
rmen2014	-	-	151	92.192	55.810	3	125.667	24.111
rmen2015	14	9	136	95.816	58.020	4	115.000	29.269
rmen2016	-	-	147	97.082	60.548	7	96.714	39.949
rmen2017	-	-	146	100.767	60.283	8	129.250	85.376
rmen2018	-	-	146	101.521	61.662	8	111.250	44.705

rmen2019	-	-	146	102.089	63.269	8	135.250	78.752
rwomen2011	22	14	132	83.583	47.182	-	-	-
rwomen2012	-	-	153	80.078	44.987	1	123.000	-
rwomen2013	19	12	134	79.642	47.593	1	133.000	-
rwomen2014	-	-	151	78.642	47.831	3	118.000	19.157
rwomen2015	14	9	136	81.338	51.586	4	114.500	20.240
rwomen2016	-	-	147	81.776	54.915	7	105.571	20.671
rwomen2017	-	-	146	85.082	54.967	8	130.500	80.711
rwomen2018	-	-	146	86.829	56.538	8	108.375	31.163
rwomen2019	-	-	146	88.500	59.903	8	132.500	87.458

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for 2012 and 2013 proportions at RCM institutions because *n*=1.

The descriptive statistics for numbers of Asian men (*rasianm*) and Asian women (*rasianw*) for assistant professors on the tenure track are presented in Table 4.8. The numbers of Asian men and Asian women assistant professors were higher at RCM institutions than non-RCM institutions. Descriptive statistics for Black or African American men (*rblackm*) and women (*rblackw*) for assistant professors on the tenure track are presented in Table 4.9. The mean numbers of Black or African American women were slightly higher at RCM institutions than non-RCM institutions. The mean numbers of Black or African American women were higher than Black or African American men. Native Hawaiian or Other Pacific Islander men (*rhawm*) and women (*rhaww*) are presented in Table 4.10; there were no Native Hawaiian or Other Pacific Islander men assistant professors at any RCM institution in this sample, so further analysis was not conducted for this group. Hispanic or Latino men (*rhispm*) and women (r*hispw*) are presented in Table 4.11; the mean number of Hispanic or Latino men and women assistant professors were slightly higher at RCM institutions in recent years. American Indian or Alaska Native men (*rnativem*) and women (*rnativew*) are presented in Table 4.12; the mean numbers of American Indian or Alaska Native men assistant professors were higher at non-RCM institutions than RCM institutions for all years, but the mean number of American Indian or Alaska Native women assistant professors was higher at RCM institutions than non-RCM institutions from FY2014 – FY2019.

Descriptive statistics for numbers of Nonresident Alien men (*rnonresm*) and women (*rnonresw*) assistant professors on the tenure track are presented in Table 4.13. The mean numbers of Nonresident Alien men and women were slightly higher or the same at RCM institutions than at non-RCM institutions. Two or More Races men (*rtwom*) and women (*rtwow*) are presented in Table 4.13, and descriptive statistics for Race/Ethnicity Unknown men (*runkm*) and women (*runkw*) are displayed in Table 4.15; the means for men and women with Race/Ethnicity Unknown were higher at RCM institutions than non-RCM institutions in FY2017 – FY2019. Finally, descriptive statistics for White men (*rwhitem*) and women (*rwhitew*) are presented in Table 4.16. The means for White men assistant professors were higher at RCM institutions than non-RCM institutions except for FY2012. The means for White women assistant professors were higher at RCM institutions than non-RCM institutions for all years in the sample.

Table 4.8

Descriptive Statistics for Asian Assistant Professors by Gender and RCM

	Missing		Non-RCM Institutions			RCM Institutions		
Variable	*n*	%	*n*	*M*	*SD*	*n*	*M*	*SD*
rasianm2011	22	14	132	13.985	11.226	-	-	-
rasianm2012	0	0	153	13.961	10.355	1	27.000	-
rasianm2013	19	12	134	13.269	10.949	1	20.000	-
rasianm2014	0	0	151	12.550	10.184	3	19.333	7.371
rasianm2015	14	9	136	12.471	9.660	4	13.250	6.397
rasianm2016	0	0	147	12.816	9.998	7	13.857	6.362
rasianm2017	0	0	146	13.781	10.331	8	17.500	6.824

rasianm2018	0	0	146	14.596	10.725	8	16.500	7.502
rasianm2019	0	0	146	14.493	10.633	8	20.500	14.909
rasianw2011	22	14	132	8.879	7.282	-	-	-
rasianw2012	0	0	153	9.078	7.057	1	22.000	-
rasianw2013	19	12	134	9.224	7.489	1	17.000	-
rasianw2014	0	0	151	8.722	7.448	3	17.000	8.718
rasianw2015	14	9	136	8.676	7.151	4	17.750	10.079
rasianw2016	0	0	147	8.776	7.578	7	13.143	6.543
rasianw2017	0	0	146	9.342	7.339	8	15.000	11.514
rasianw2018	0	0	146	9.815	7.998	8	12.750	4.367
rasianw2019	0	0	146	10.144	8.445	8	18.375	18.715

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for 2012 and 2013 proportions at RCM institutions because *n*=1.

Table 4.9

Descriptive Statistics for Black Assistant Professors by Gender and RCM

	Missing		Non-RCM Institutions			RCM Institutions		
Variable	*n*	%	*n*	*M*	*SD*	*n*	*M*	*SD*
rblackm2011	22	14	132	4.197	4.297	-	-	-
rblackm2012	-	-	153	3.765	4.071	1	7.000	-
rblackm2013	19	12	134	3.672	3.680	1	5.000	-
rblackm2014	-	-	151	3.258	3.255	3	4.333	3.055
rblackm2015	14	9	136	3.529	3.275	4	4.750	3.594
rblackm2016	-	-	147	3.510	3.044	7	2.571	1.813
rblackm2017	-	-	146	3.849	3.673	8	2.875	1.458
rblackm2018	-	-	146	4.068	3.790	8	3.250	2.188
rblackm2019	-	-	146	4.048	3.988	8	3.750	2.252
rblackw2011	22	14	132	5.909	6.563	-	-	-
rblackw2012	-	-	153	5.399	6.311	1	8.000	-
rblackw2013	19	12	134	5.328	5.844	1	7.000	-
rblackw2014	-	-	151	5.046	5.731	3	8.000	3.606
rblackw2015	14	9	136	5.625	5.693	4	7.500	2.887
rblackw2016	-	-	147	5.231	5.599	7	6.857	3.024

rblackw2017	-	-	146	5.685	6.156	8	8.000	3.381
rblackw2018	-	-	146	5.925	5.935	8	8.125	3.834
rblackw2019	-	-	146	5.842	5.855	8	8.750	2.915

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for 2012 and 2013 proportions at RCM institutions because *n*=1.

Table 4.10

Descriptive Statistics for Native Hawaiian Assistant Professors by Gender and RCM

	Missing		Non-RCM Institutions			RCM Institutions		
Variable	*n*	%	*n*	*M*	*SD*	*n*	*M*	*SD*
rhawm2011	21	14	133	0.045	0.208	-	-	-
rhawm2012	-	-	153	0.072	0.488	1	0.000	-
rhawm2013	19	12	134	0.134	0.891	1	0.000	.
rhawm2014	-	-	151	0.106	0.759	3	0.000	0.000
rhawm2015	13	8	137	0.095	0.629	4	0.000	0.000
rhawm2016	-	-	147	0.075	0.455	7	0.000	0.000
rhawm2017	-	-	146	0.082	0.362	8	0.000	0.000
rhawm2018	-	-	146	0.082	0.343	8	0.000	0.000
rhawm2019	-	-	146	0.075	0.354	8	0.000	0.000
rhaww2011	21	14	133	0.023	0.149	-	-	-
rhaww2012	-	-	153	0.412	3.478	1	0.000	-
rhaww2013	19	12	134	0.157	1.068	1	0.000	-
rhaww2014	-	-	151	0.159	1.027	3	0.000	0.000
rhaww2015	13	8	137	0.175	1.163	4	0.000	0.000
rhaww2016	-	-	147	0.150	1.106	7	0.143	0.378
rhaww2017	-	-	146	0.144	1.030	8	0.250	0.463
rhaww2018	-	-	146	0.144	1.024	8	0.250	0.463
rhaww2019	-	-	146	0.151	0.949	8	0.250	0.463

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for 2012 and 2013 proportions at RCM institutions because *n*=1.

Table 4.11

Descriptive Statistics for Hispanic or Latino Assistant Professors by Gender and RCM

	Missing		Non-RCM Institutions			RCM Institutions		
Variable	*n*	%	*n*	*M*	*SD*	*n*	*M*	*SD*
rhispm2011	21	14	133	4.692	5.041	-	-	-
rhispm2012	-	-	153	4.255	4.277	1	5.000	-
rhispm2013	19	12	134	4.291	4.032	1	4.000	-
rhispm2014	-	-	151	4.424	4.411	3	4.000	1.732
rhispm2015	13	8	137	4.431	4.404	4	3.500	1.732
rhispm2016	-	-	147	4.571	4.696	7	4.000	2.082
rhispm2017	-	-	146	5.110	5.233	8	6.000	3.742
rhispm2018	-	-	146	5.336	5.288	8	6.250	6.228
rhispm2019	-	-	146	5.384	5.377	8	7.000	6.347
rhispw2011	21	14	133	4.414	4.634	-	-	-
rhispw2012	-	-	153	4.209	4.556	1	6.000	-
rhispw2013	19	12	134	4.172	4.154	1	5.000	-
rhispw2014	-	-	151	4.185	4.261	3	4.333	1.528
rhispw2015	13	8	137	4.226	4.539	4	5.250	2.872
rhispw2016	-	-	147	4.435	5.060	7	6.286	3.039
rhispw2017	-	-	146	4.788	5.225	8	6.125	4.704
rhispw2018	-	-	146	5.110	5.405	8	6.375	5.553
rhispw2019	-	-	146	5.295	5.626	8	7.625	6.046

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for 2012 and 2013 proportions at RCM institutions because *n*=1.

Table 4.12

Descriptive Statistics for Native American Assistant Professors by Gender and RCM

	Missing		Non-RCM Institutions			RCM Institutions		
Variable	*N*	%	*n*	*M*	*SD*	*N*	*M*	*SD*
rnativem2011	21	14	133	0.376	0.784	-	-	-
rnativem2012	-	-	153	0.359	0.775	1	0.000	-
rnativem2013	19	12	134	0.373	0.712	1	0.000	-

rnativem2014	-	-	151	0.338	0.631	3	0.000	0.000
rnativem2015	13	8	137	0.401	0.732	4	0.250	0.500
rnativem2016	-	-	147	0.333	0.655	7	0.143	0.378
rnativem2017	-	-	146	0.342	0.637	8	0.125	0.354
rnativem2018	-	-	146	0.363	0.586	8	0.125	0.354
rnativem2019	-	-	146	0.315	0.619	8	0.250	0.463
rnativew2011	21	14	133	0.519	0.958	-	-	-
rnativew2012	-	-	153	0.523	0.946	1	0.000	-
rnativew2013	19	12	134	0.470	0.838	1	0.000	-
rnativew2014	-	-	151	0.457	0.985	3	1.000	1.732
rnativew2015	13	8	137	0.409	0.879	4	0.500	0.577
rnativew2016	-	-	147	0.442	0.900	7	0.714	0.756
rnativew2017	-	-	146	0.445	0.902	8	1.000	1.690
rnativew2018	-	-	146	0.397	0.826	8	0.500	0.756
rnativew2019	-	-	146	0.411	0.844	8	1.000	1.773

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for 2012 and 2013 proportions at RCM institutions because *n*=1.

Table 4.13

Descriptive Statistics for Nonresident Alien Assistant Professors by Gender and RCM

	Missing		Non-RCM Institutions			RCM Institutions		
Variable	*n*	%	*n*	*M*	*SD*	*n*	*M*	*SD*
rnonresm2011	21	14	133	13.617	14.169	-	-	-
rnonresm2012	-	-	153	12.261	12.899	1	26.000	-
rnonresm2013	19	12	134	12.194	9.657	1	23.000	-
rnonresm2014	-	-	151	12.152	10.654	3	16.333	8.145
rnonresm2015	13	8	137	13.569	10.860	4	22.750	20.106
rnonresm2016	-	-	147	14.544	13.134	7	13.143	10.399
rnonresm2017	-	-	146	15.568	12.555	8	24.125	30.801
rnonresm2018	-	-	146	15.630	11.743	8	16.125	14.837
rnonresm2019	-	-	146	16.870	13.221	8	17.875	12.506
rnonresw2011	21	14	133	7.519	7.827	-	-	-
rnonresw2012	-	-	153	6.732	7.266	1	10.000	-

rnonresw2013	19	12	134	7.291	6.161	1	15.000	-
rnonresw2014	-	-	151	7.219	6.516	3	12.333	1.155
rnonresw2015	13	8	137	7.876	6.086	4	15.000	11.402
rnonresw2016	-	-	147	8.252	7.620	7	8.143	7.335
rnonresw2017	-	-	146	8.637	6.437	8	17.000	24.018
rnonresw2018	-	-	146	9.151	6.331	8	9.125	7.936
rnonresw2019	-	-	146	9.575	7.041	8	11.125	9.015

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for 2012 and 2013 proportions at RCM institutions because *n*=1.

Table 4.14

Descriptive Statistics for Two or More Races Assistant Professors by Gender and RCM

	Missing		Non-RCM Institutions			RCM Institutions		
Variable	*n*	%	*n*	*M*	*SD*	*n*	*M*	*SD*
rtwom2011	22	14	132	0.545	1.094	-	-	-
rtwom2012	1	1	152	0.487	0.899	1	0.000	-
rtwom2013	19	12	134	0.485	0.956	1	0.000	-
rtwom2014	1	1	150	0.573	0.965	3	0.667	1.155
rtwom2015	13	8	137	0.723	0.976	4	0.750	1.500
rtwom2016	1	1	146	0.952	1.450	7	0.714	1.254
rtwom2017	1	1	145	1.034	1.371	8	1.250	1.581
rtwom2018	1	1	145	0.972	1.236	8	1.000	1.195
rtwom2019	1	1	145	1.076	1.349	8	1.125	1.356
rtwow2011	21	14	133	0.617	0.927	-	-	-
rtwow2012	-	-	153	0.680	1.011	1	1.000	-
rtwow2013	19	12	134	0.731	1.020	1	2.000	-
rtwow2014	-	-	151	0.887	1.247	3	1.333	1.155
rtwow2015	13	8	137	1.000	1.393	4	1.750	1.258
rtwow2016	-	-	147	1.170	1.780	7	1.143	0.900
rtwow2017	-	-	146	1.158	1.622	8	2.125	2.532
rtwow2018	-	-	146	1.240	1.510	8	0.875	1.126
rtwow2019	-	-	146	1.288	1.593	8	1.375	1.506

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for 2012 and 2013 proportions at RCM institutions because *n*=1.

Table 4.15

Descriptive Statistics for Race/Ethnicity Unknown Assistant Professors by Gender and RCM

	Missing		Non-RCM Institutions			RCM Institutions		
Variable	*n*	%	*n*	*M*	*SD*	*n*	*M*	*SD*
runkm2011	21	14	133	3.857	8.107	-	-	-
runkm2012	-	-	153	3.680	7.715	1	1.000	-
runkm2013	19	12	134	3.627	6.981	1	10.000	-
runkm2014	-	-	151	4.947	9.526	3	1.667	2.082
runkm2015	13	8	137	5.693	10.879	4	1.500	2.380
runkm2016	-	-	147	5.653	10.976	7	3.857	8.474
runkm2017	-	-	146	5.788	10.445	8	7.750	11.732
runkm2018	-	-	146	5.911	12.085	8	8.500	14.142
runkm2019	-	-	146	6.199	12.773	8	12.875	19.967
runkw2011	21	14	133	2.955	6.098	-	-	-
runkw2012	-	-	153	2.993	6.036	1	0.000	-
runkw2013	19	12	134	3.201	6.950	1	25.000	-
runkw2014	-	-	151	4.185	8.611	3	0.667	1.155
runkw2015	13	8	137	4.701	9.433	4	0.750	1.500
runkw2016	-	-	147	4.673	9.510	7	5.143	10.205
runkw2017	-	-	146	5.055	10.464	8	7.125	11.344
runkw2018	-	-	146	4.925	11.459	8	7.375	12.694
runkw2019	-	-	146	5.240	12.398	8	9.250	15.341

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for 2012 and 2013 proportions at RCM institutions because *n*=1.

Table 4.16

Descriptive Statistics for White Assistant Professors by Gender and RCM

	Missing		Non-RCM Institutions			RCM Institutions		
Variable	*n*	%	*n*	*M*	*SD*	*n*	*M*	*SD*
rwhitem2011	21	14	133	62.782	39.947	-	-	-
rwhitem2012	-	-	153	57.856	35.674	1	66.000	-
rwhitem2013	19	12	134	56.313	37.454	1	51.000	-

rwhitem2014	-	-	151	53.848	36.344	3	79.333	12.662
rwhitem2015	13	8	137	54.547	37.406	4	68.250	22.736
rwhitem2016	-	-	147	54.585	37.388	7	58.429	26.582
rwhitem2017	-	-	146	55.233	36.252	8	69.625	42.715
rwhitem2018	-	-	146	54.541	35.457	8	59.500	26.126
rwhitem2019	-	-	146	53.705	35.734	8	71.875	43.172
rwhitew2011	21	14	133	52.534	31.342	-	-	-
rwhitew2012	-	-	153	49.889	30.290	1	76.000	-
rwhitew2013	19	12	134	48.993	31.845	1	62.000	-
rwhitew2014	-	-	151	47.781	31.852	3	73.333	2.887
rwhitew2015	13	8	137	48.482	34.117	4	66.000	9.416
rwhitew2016	-	-	147	48.701	35.544	7	64.000	11.387
rwhitew2017	-	-	146	49.890	35.475	8	73.875	38.835
rwhitew2018	-	-	154	50.864	33.903	8	63.000	18.883
rwhitew2019	-	-	146	50.651	36.277	8	74.750	42.500

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for 2012 and 2013 proportions at RCM institutions because *n*=1.

Descriptive Statistics for ASEE Analyses

The descriptive statistics for the key variables for RQ3 (*number of assistant professors of engineering when considering gender*) are provided in Tables 4.17 – 4.22. The descriptive statistics for the number of engineering assistant professors (*engasst*) are provided in Table 4.17, the descriptive statistics for the number of men engineering assistant professors (*engasstm*) are displayed in Table 4.18, and descriptive statistics for number of women engineering assistant professors (*engasstw*) are displayed in Table 4.19.

Table 4.17

Descriptive Statistics for Number of Engineering Assistant Professors

	Missing						
Variable	*n*	%	*n*	*M*	*SD*	Minimum	Maximum
Non-RCM Institutions							
engasst2011	-	-	117	22.564	15.570	0	94
engasst2012	-	-	116	22.172	15.530	2	96
engasst2013	-	-	116	21.147	13.978	3	78
engasst2014	-	-	114	21.675	14.515	3	76
engasst2015	-	-	113	22.469	15.311	3	72
engasst2016	-	-	110	23.573	16.796	0	75
engasst2017	-	-	109	24.991	18.468	0	93
engasst2018	-	-	109	27.431	20.521	0	106
engasst2019	7	6.420	102	30.735	21.677	2	106
RCM Institutions							
engasst2012	-	-	1	29.000	-	29	29
engasst2013	-	-	1	31.000	-	31	31
engasst2014	-	-	3	19.333	7.024	12	26
engasst2015	-	-	4	19.250	8.342	12	31
engasst2016	-	-	7	21.714	7.477	12	32
engasst2017	-	-	8	20.750	9.513	3	33
engasst2018	-	-	8	32.250	7.797	20	45
engasst2019	-	-	8	37.250	9.377	21	50

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for engasst2012 and engasst2013 because *n*=1.

Table 4.18

Descriptive Statistics for Men Engineering Assistant Professors by RCM

Variable	Missing	*n*	*M*	*SD*	Minimum	Maximum
Non-RCM Institutions						
engasstm2011	-	117	17.940	12.045	0	71
engasstm2012	-	116	17.414	11.919	1	66

engasstm2013	-	116	16.534	10.686	2	58
engasstm2014	-	114	16.798	11.009	2	59
engasstm2015	-	113	17.504	11.491	2	53
engasstm2016	-	110	18.427	12.766	0	57
engasstm2017	-	109	19.569	14.128	0	64
engasstm2018	-	109	21.523	15.637	0	73
engasstm2019	7	102	23.549	16.098	1	77
RCM Institutions						
engasstm2012	-	1	24.000	-	24	24
engasstm2013	-	1	27.000	-	27	27
engasstm2014	-	3	17.000	5.568	11	22
engasstm2015	-	4	16.250	5.909	12	25
engasstm2016	-	7	17.286	5.736	11	25
engasstm2017	-	8	16.875	6.728	3	26
engasstm2018	-	8	26.375	6.632	17	39
engasstm2019	-	8	29.875	8.254	18	43

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for engasstm2012 and engasstm2013 because *n*=1.

Table 4.19

Descriptive Statistics for Women Engineering Assistant Professors by RCM

Variable	Missing	*n*	*M*	*SD*	Minimum	Maximum
Non-RCM Institutions						
engasstw2011	-	117	4.624	4.110	0	28
engasstw2012	-	116	4.759	4.176	0	30
engasstw2013	-	116	4.612	4.000	0	23
engasstw2014	-	114	4.877	4.311	0	22
engasstw2015	-	113	4.965	4.496	0	20
engasstw2016	-	110	5.145	4.783	0	24
engasstw2017	-	109	5.422	5.154	0	29
engasstw2018	-	109	5.908	5.734	0	33
engasstw2019	7	102	7.186	6.283	0	33
RCM Institutions						
engasstw2012	-	1	5.000	.	5	5

engasstw2013	-	1	4.000	.	4	4
engasstw2014	-	3	2.333	1.528	1	4
engasstw2015	-	4	3.000	2.944	0	6
engasstw2016	-	7	4.429	2.440	1	7
engasstw2017	-	8	3.875	3.271	0	9
engasstw2018	-	8	5.875	3.643	2	13
engasstw2019	-	8	7.375	3.503	3	13

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for engasst2012 and engasst2013 because *n*=1.

Region served a fixed variable and covariate to address RQ3. The eight BEA regional classifications that included institutions in the RQ3 sample were New England, Mid East, Great Lakes, Plains, Southeast, Southwest, Rocky Mountains, and Far West. The number and percentage of institutions in the sample for RQ3 in the eight regions are displayed in Table 4.20.

Table 4.20

Number and Percentage of Institutions in Each Region

Region	*n*	%
New England	7	6
Mid East	10	9
Great Lakes	15	13
Plains	10	9
Southeast	32	27
Southwest	17	15
Rocky Mtns	7	6
Far West	19	16
Total	117	100

Note. Percentages are rounded to the nearest whole number

The results of tests of normality for number of engineering assistant professors (engasst), number of men engineering assistant professors (engasstm), and number of women engineering assistant professors (engasstw) are presented in Table 4.21. I rejected the hypothesis that the distributions for numbers of engineering assistant professors and numbers of engineering assistant professors by gender were normal for all years as $p<0.05$. Based on the p-values for Kurtosis, I rejected the hypotheses that distributions for numbers of engineering assistant professors (except 2016), numbers of men engineering assistant professors (except 2016), and numbers of women engineering assistant professors were normal for all years at $p<0.05$. Based on the combined adjusted Chi-square test, I rejected that the hypothesis that the distribution was normal for all variables. As numbers of faculty members cannot be less than zero, distributions that were not normal and positively skewed were expected.

Table 4.21

Tests for Normality for Engineering Assistant Professors by Gender and RCM

Variable	*n*	Skewness (*p*)	Kurtosis (*p*)	Adjusted X^2	*p*
engasst2011	117	0.000*	0.000*	45.510	0.000*
engasst2012	117	0.000*	0.000*	46.360	0.000*
engasst2013	117	0.000*	0.000*	33.180	0.000*
engasst2014	117	0.000*	0.001*	27.480	0.000*
engasst2015	117	0.000*	0.015*	21.880	0.000*
engasst2016	117	0.000*	0.074	17.720	0.000*
engasst2017	117	0.000*	0.004*	26.010	0.000*
engasst2018	117	0.000*	0.001*	28.960	0.000*
engasst2019	110	0.000*	0.002*	26.600	0.000*
engasstm2011	117	0.000*	0.000*	34.650	0.000*
engasstm2012	117	0.000*	0.000*	36.070	0.000*
engasstm2013	117	0.000*	0.001*	28.100	0.000*
engasstm2014	117	0.000*	0.004*	22.680	0.000*
engasstm2015	117	0.000*	0.027*	18.970	0.000*
engasstm2016	117	0.000*	0.133	15.370	0.001*
engasstm2017	117	0.000*	0.039*	19.710	0.000*
engasstm2018	117	0.000*	0.037*	18.670	0.000*

engasstm2019	110	0.000*	0.015*	20.300	0.000*
engasstw2011	117	0.000*	0.000*	64.810	0.000*
engasstw2012	117	0.000*	0.000*	66.420	0.000*
engasstw2013	117	0.000*	0.000*	43.600	0.000*
engasstw2014	117	0.000*	0.000*	42.250	0.000*
engasstw2015	117	0.000*	0.000*	36.560	0.000*
engasstw2016	117	0.000*	0.000*	35.590	0.000*
engasstw2017	117	0.000*	0.000*	43.870	0.000*
engasstw2018	117	0.000*	0.000*	51.840	0.000*
engasstw2019	110	0.000*	0.000*	35.380	0.000*

Note. Significant at $*p<0.05$. P-values are displayed in Skewness and Kurtosis columns.

The descriptive statistics for the key variables for RQ3a (*number of assistant professors of engineering when considering gender and race/ethnicity*) are provided in Tables 4.22 – 4.30. Descriptive statistics for men and women assistant professors of engineering by Asian American (*raamm* and *raamw*; Table 4.22), Black or African American (*rafm* and *rafw*; Table 4.23), Native Hawaiian or Other Pacific Islander (*rhawm* and *rhaww*; Table 4.24), Hispanic or Latino (*rhispm* and *rhispw*; Table 4.25), American Indian or Alaskan Native (*rnatm* and *rnatw*; Table 4.26), Race/Ethnicity: Other (*rom* and *row*; Table 4.27), Two or More Races (*rtwom* and *rtwow*; Table 4.28), Race/Ethnicity Unknown (*runkm* and *runkw*; Table 4.29), and Caucasian/White (*rwm* and *rww*; Table 4.30) gender and race/ethnicity proportions by RCM implementation are displayed in this section. As with prior research questions, since numbers of faculty were influenced by institution size, I converted total numbers of assistant professors of engineering into proportions, renaming proportion variables with the following convention, for example: rwm2019 became pwm2019.

Table 4.22

Descriptive Statistics for Asian American Engineering Assistant Professors by Gender

Variable	*n*	*M*	*SD*	Variable	*n*	*M*	*SD*
Non-RCM Institutions							
raamm2011	117	6.462	5.696	raamw2011	117	1.419	1.504
raamm2012	116	6.302	5.370	raamw2012	116	1.440	1.556
raamm2013	116	5.819	4.944	raamw2013	116	1.302	1.476
raamm2014	114	5.754	4.916	raamw2014	114	1.342	1.739
raamm2015	113	5.628	4.870	raamw2015	113	1.336	1.590
raamm2016	110	6.155	5.615	raamw2016	110	1.464	1.785
raamm2017	109	6.560	5.816	raamw2017	109	1.477	1.703
raamm2018	109	7.404	6.438	raamw2018	109	1.651	1.766
raamm2019	102	8.304	7.074	raamw2019	102	2.039	1.908
RCM Institutions							
raamm2012	1	16.000	-	raamw2012	1	1.000	-
raamm2013	1	4.000	-	raamw2013	1	0.000	-
raamm2014	3	4.667	2.082	raamw2014	3	0.667	0.577
raamm2015	4	3.000	1.155	raamw2015	4	0.500	0.577
raamm2016	7	5.857	4.776	raamw2016	7	1.571	0.976
raamm2017	8	6.250	5.203	raamw2017	8	1.250	1.389
raamm2018	8	8.625	6.760	raamw2018	8	1.500	1.414
raamm2019	8	8.500	5.237	raamw2019	8	1.625	1.768

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for 2012 and 2013 because *n*=1.

Table 4.23

Descriptive Statistics for African American Engineering Assistant Professors by Gender

Variable	*n*	*M*	*SD*	Variable	*n*	*M*	*SD*
Non-RCM Institutions							
rafm2011	117	0.513	0.988	rafw2011	117	0.265	0.687
rafm2012	116	0.578	0.988	rafw2012	116	0.241	0.504
rafm2013	116	0.509	0.880	rafw2013	116	0.216	0.507
rafm2014	114	0.456	0.843	rafw2014	114	0.219	0.511
rafm2015	113	0.487	1.364	rafw2015	113	0.230	0.535
rafm2016	110	0.445	0.904	rafw2016	110	0.155	0.411
rafm2017	109	0.394	0.720	rafw2017	109	0.183	0.434
rafm2018	109	0.413	0.670	rafw2018	109	0.174	0.468
rafm2019	102	0.373	0.716	rafw2019	102	0.235	0.566
RCM Institutions							
rafm2012	1	0.000	-	rafw2012	1	0.000	-
rafm2013	1	0.000	-	rafw2013	1	0.000	-
rafm2014	3	0.000	0.000	rafw2014	3	0.000	0.000
rafm2015	4	0.250	0.500	rafw2015	4	0.000	0.000
rafm2016	7	0.286	0.488	rafw2016	7	0.143	0.378
rafm2017	8	0.500	0.535	rafw2017	8	0.000	0.000
rafm2018	8	0.250	0.463	rafw2018	8	0.125	0.354
rafm2019	8	0.625	0.744	rafw2019	8	0.250	0.463

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for 2012 and 2013 because *n*=1.

Table 4.24

Descriptive Statistics for Native Hawaiian Engineering Assistant Professors by Gender

Variable	*n*	*M*	*SD*	Variable	*n*	*M*	*SD*
Non-RCM Institutions							
rhawm2011	117	0.000	0.000	rhaw2011	117	0.017	0.130
rhawm2012	116	0.009	0.093	rhaw2012	116	0.009	0.093
rhawm2013	116	0.043	0.464	rhaw2013	116	0.000	0.000

rhawm2014	114	0.009	0.094	rhaw2014	114	0.009	0.094
rhawm2015	113	0.027	0.210	rhaw2015	113	0.027	0.161
rhawm2016	110	0.055	0.425	rhaw2016	110	0.045	0.314
rhawm2017	109	0.018	0.135	rhaw2017	109	0.018	0.135
rhawm2018	109	0.028	0.213	rhaw2018	109	0.028	0.164
rhawm2019	102	0.010	0.099	rhaw2019	102	0.029	0.170
RCM Institutions							
rhawm2012	1	0.000	-	rhaw2012	1	0.000	-
rhawm2013	1	0.000	-	rhaw2013	1	0.000	-
rhawm2014	3	0.000	0.000	rhaw2014	3	0.000	0.000
rhawm2015	4	0.000	0.000	rhaw2015	4	0.000	0.000
rhawm2016	7	0.000	0.000	rhaw2016	7	0.000	0.000
rhawm2017	8	0.000	0.000	rhaw2017	8	0.000	0.000
rhawm2018	8	0.000	0.000	rhaw2018	8	0.000	0.000
rhawm2019	8	0.000	0.000	rhaw2019	8	0.000	0.000

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for 2012 and 2013 because *n*=1.

Table 4.25

Descriptive Statistics for Hispanic Engineering Assistant Professors by Gender

Variable	*n*	*M*	*SD*	Variable	*n*	*M*	*SD*
Non-RCM Institutions							
rhispm2011	117	0.573	1.220	rhispw2011	117	0.239	0.552
rhispm2012	116	0.509	1.075	rhispw2012	116	0.198	0.514
rhispm2013	116	0.509	0.937	rhispw2013	116	0.241	0.521
rhispm2014	114	0.465	0.843	rhispw2014	114	0.254	0.529
rhispm2015	113	0.425	0.754	rhispw2015	113	0.248	0.575
rhispm2016	110	0.491	0.843	rhispw2016	110	0.255	0.582
rhispm2017	109	0.523	0.800	rhispw2017	109	0.239	0.559
rhispm2018	109	0.670	0.913	rhispw2018	109	0.275	0.591
rhispm2019	102	0.843	1.124	rhispw2019	102	0.304	0.541
RCM Institutions							
rhispm2012	1	0.000	-	rhispw2012	1	2.000	-

rhispm2013	1	0.000	.	rhispw2013	1	1.000	-
rhispm2014	3	0.000	0.000	rhispw2014	3	0.333	0.577
rhispm2015	4	0.000	0.000	rhispw2015	4	0.250	0.500
rhispm2016	7	0.429	0.787	rhispw2016	7	0.143	0.378
rhispm2017	8	0.250	0.707	rhispw2017	8	0.375	0.518
rhispm2018	8	1.000	1.414	rhispw2018	8	0.500	0.926
rhispm2019	8	1.000	1.414	rhispw2019	8	0.625	0.744

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for 2012 and 2013 because *n*=1.

Table 4.26

Descriptive Statistics for American Indian Engineering Assistant Professors by Gender

Variable	*n*	*M*	*SD*	Variable	*n*	*M*	*SD*
Non-RCM Institutions							
rnatm2011	117	0.017	0.130	rnatw2011	117	0.026	0.206
rnatm2012	116	0.069	0.367	rnatw2012	116	0.017	0.131
rnatm2013	116	0.078	0.496	rnatw2013	116	0.026	0.207
rnatm2014	114	0.044	0.245	rnatw2014	114	0.000	0.000
rnatm2015	113	0.053	0.225	rnatw2015	113	0.000	0.000
rnatm2016	110	0.018	0.134	rnatw2016	110	0.009	0.095
rnatm2017	109	0.037	0.189	rnatw2017	109	0.018	0.135
rnatm2018	109	0.101	0.384	rnatw2018	109	0.009	0.096
rnatm2019	102	0.049	0.217	rnatw2019	102	0.010	0.099
RCM Institutions							
rnatm2012	1	0.000	-	rnatw2012	1	0.000	-
rnatm2013	1	0.000	-	rnatw2013	1	0.000	-
rnatm2014	3	0.000	0.000	rnatw2014	3	0.000	0.000
rnatm2015	4	0.000	0.000	rnatw2015	4	0.000	0.000
rnatm2016	7	0.000	0.000	rnatw2016	7	0.000	0.000
rnatm2017	8	0.000	0.000	rnatw2017	8	0.000	0.000
rnatm2018	8	0.000	0.000	rnatw2018	8	0.000	0.000
rnatm2019	8	0.000	0.000	rnatw2019	8	0.000	0.000

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for 2012 and 2013 because *n*=1.

Table 4.27

Descriptive Statistics for Race: Other Engineering Assistant Professors by Gender

Variable	*n*	*M*	*SD*	Variable	*n*	*M*	*SD*
Non-RCM Institutions							
rom2011	117	2.128	5.330	row2011	117	0.470	1.356
rom2012	116	0.000	0.000	row2012	116	0.000	0.000
rom2013	116	0.000	0.000	row2013	116	0.000	0.000
rom2014	114	0.000	0.000	row2014	114	0.000	0.000
rom2015	113	0.000	0.000	row2015	113	0.000	0.000
rom2016	110	0.000	0.000	row2016	110	0.000	0.000
rom2017	109	0.000	0.000	row2017	109	0.000	0.000
rom2018	109	0.000	0.000	row2018	109	0.000	0.000
rom2019	102	0.000	0.000	row2019	102	0.000	0.000
RCM Institutions							
rom2012	1	0.000	-	row2012	1	0.000	-
rom2013	1	0.000	-	row2013	1	0.000	-
rom2014	3	0.000	0.000	row2014	3	0.000	0.000
rom2015	4	0.000	0.000	row2015	4	0.000	0.000
rom2016	7	0.000	0.000	row2016	7	0.000	0.000
rom2017	8	0.000	0.000	row2017	8	0.000	0.000
rom2018	8	0.000	0.000	row2018	8	0.000	0.000
rom2019	8	0.000	0.000	row2019	8	0.000	0.000

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for 2012 and 2013 because *n*=1.

Table 4.28

Descriptive Statistics for Two or More Races Engineering Assistant Professors by Gender

Variable	*n*	*M*	*SD*	Variable	*n*	*M*	*SD*
Non-RCM Institutions							
rtwom2011	117	0.000	0.000	rtwow2011	117	0.000	0.000
rtwom2012	116	0.009	0.093	rtwow2012	116	0.017	0.131
rtwom2013	116	0.078	0.420	rtwow2013	116	0.026	0.159

rtwom2014	114	0.053	0.261	rtwow2014	114	0.044	0.206
rtwom2015	113	0.088	0.606	rtwow2015	113	0.071	0.320
rtwom2016	110	0.055	0.265	rtwow2016	110	0.045	0.209
rtwom2017	109	0.083	0.308	rtwow2017	109	0.055	0.229
rtwom2018	109	0.073	0.424	rtwow2018	109	0.046	0.210
rtwom2019	102	0.069	0.254	rtwow2019	102	0.078	0.364
RCM Institutions							
rtwom2012	1	0.000	-	rtwow2012	1	0.000	-
rtwom2013	1	0.000	-	rtwow2013	1	0.000	-
rtwom2014	3	0.000	0.000	rtwow2014	3	0.000	0.000
rtwom2015	4	0.000	0.000	rtwow2015	4	0.000	0.000
rtwom2016	7	0.857	2.268	rtwow2016	7	0.143	0.378
rtwom2017	8	0.000	0.000	rtwow2017	8	0.000	0.000
rtwom2018	8	0.125	0.354	rtwow2018	8	0.000	0.000
rtwom2019	8	0.125	0.354	rtwow2019	8	0.000	0.000

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for 2012 and 2013 because *n*=1.

Table 4.29

Descriptive Statistics for Race Unknown Engineering Assistant Professors by Gender

Variable	*n*	*M*	*SD*	Variable	*n*	*M*	*SD*
Non-RCM Institutions							
runkm2011	117	0.000	0.000	runkw2011	117	0.000	0.000
runkm2012	116	1.845	4.891	runkw2012	116	0.448	1.398
runkm2013	116	1.991	5.299	runkw2013	116	0.543	1.360
runkm2014	114	2.316	5.893	runkw2014	114	0.693	1.771
runkm2015	113	2.770	5.892	runkw2015	113	0.735	1.885
runkm2016	110	3.055	6.824	runkw2016	110	0.791	1.926
runkm2017	109	3.229	7.182	runkw2017	109	0.872	2.253
runkm2018	109	3.578	8.047	runkw2018	109	0.899	2.677
runkm2019	102	4.000	7.806	runkw2019	102	1.245	3.148
RCM Institutions							
runkm2012	1	0.000	-	runkw2012	1	0.000	-

runkm2013	1	15.000	-	runkw2013	1	2.000	-
runkm2014	3	3.333	5.774	runkw2014	3	0.667	1.155
runkm2015	4	3.500	7.000	runkw2015	4	1.000	2.000
runkm2016	7	2.714	5.529	runkw2016	7	0.714	1.890
runkm2017	8	2.375	5.181	runkw2017	8	0.250	0.707
runkm2018	8	7.375	10.197	runkw2018	8	1.375	2.504
runkm2019	8	7.250	9.513	runkw2019	8	1.625	1.598

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for 2012 and 2013 because *n*=1.

Table 4.30

Descriptive Statistics for White Engineering Assistant Professors by Gender

Variable	*n*	*M*	*SD*	Variable	*n*	*M*	*SD*
Non-RCM Institutions							
rwm2011	117	8.248	7.249	rww2011	117	2.188	2.776
rwm2012	116	8.095	6.913	rww2012	116	2.388	2.692
rwm2013	116	7.509	6.325	rww2013	116	2.259	2.478
rwm2014	114	7.702	6.504	rww2014	114	2.316	2.532
rwm2015	113	8.027	6.691	rww2015	113	2.319	2.589
rwm2016	110	8.155	7.126	rww2016	110	2.382	2.989
rwm2017	109	8.725	7.651	rww2017	109	2.560	3.104
rwm2018	109	9.257	8.072	rww2018	109	2.826	3.442
rwm2019	102	9.902	8.510	rww2019	102	3.245	3.929
RCM Institutions							
rwm2012	1	8.000	-	rww2012	1	2.000	-
rwm2013	1	8.000	-	rww2013	1	1.000	-
rwm2014	3	9.000	1.732	rww2014	3	0.667	0.577
rwm2015	4	9.500	1.291	rww2015	4	1.250	1.893
rwm2016	7	7.143	4.018	rww2016	7	1.714	1.704
rwm2017	8	7.500	4.928	rww2017	8	2.000	2.138
rwm2018	8	9.000	6.047	rww2018	8	2.375	2.560
rwm2019	8	12.375	7.708	rww2019	8	3.250	2.816

Note. Institutions that implemented RCM in FY2011 were not included in the sample. *SD* is not available for RCM institutions for 2012 and 2013 because *n*=1.

Descriptive Statistics for Engineering Ohio Analyses

Descriptive statistics for the key variables for RQ4 (*relationship between RCM implementation and annual salaries of assistant professors of engineering at public doctoral universities in Ohio*) are provided in Table 4.31. The mean salaries of assistant professors of engineering at Ohio University rose during the time period in which RCM was implemented and then declined. Further analysis was intended to identify if the change in average salary can be attributed to RCM implementation. The results of the nearest neighbor statistical matching process are presented in the next sections. Then an evaluation of matched samples, flexible conditional difference-in-difference estimation models, and fixed effects difference-in-difference estimation models are described.

Table 4.31

Descriptive Statistics for Annual Salary of Ohio Engineering Assistant Professors

Year	RCM	*n*	*M*	*SD*	Minimum	Maximum
University of Toledo						
2011	no	13	85325	17353	64087	126201
2012	no	10	110356	23560	65405	135970
2013	no	4	94220	4860	88789	100456
2014	no	7	90096	25181	51436	120464
2015	no	4	103113	23525	80257	132970
2016	no	8	93950	18383	78293	133303
2017	no	14	97273	15182	78586	132718
Ohio University						
2011	no	6	84046	10567	65447	95366
2012	no	12	76165	12830	49447	94456
2013	no	11	82681	24989	32952	111159
2014	yes	7	106754	26438	61227	135555
2015	yes	18	93058	31614	38950	134359
2016	yes	12	87884	20331	30597	116533

2017	yes	10	88285	3719	80644	95348

Note. Ohio University implemented RCM in FY 2014.

Below are the results from nearest neighbor statistical matching processes and difference-in-difference estimations of IPEDS, ASEE, and Ohio data.

Results from IPEDS Analyses

The results of nearest-neighbor matching processes and difference-in-difference estimations of institutional average of salary, salary by gender, institutional proportions by gender and by gender and race/ethnicity proportions for assistant professors on the tenure track by RCM implementation are presented in this section. Prior to matching, the analytic sample for IPEDS analysis was 1,386 and after matching the analytic sample was 144. For RQ1 (*average salary of assistant professors*), the dependent variable (outcome) was *nsalary*, the annual natural log of institutional average salary indexed to FY2019 values for assistant professors on the tenure-track equated to a 9-month contract at public, research doctoral universities. For RQ1, there were eight treated (RCM) universities and 146 control (non-RCM) universities for a total sample of 154 universities. The nearest neighbor statistical matching process identified one non-treated (control) university for each of the eight treated (RCM) universities. Table 4.32 shows the results of the nearest neighbor statistical distance matching process for nsalary.

Table 4.32

Institutional Matched Sample for Average Salary of Assistant Professors

	Year	RCM Institution	Non-RCM Institution
1	2012	Texas Tech University	Old Dominion University
2	2014	Auburn University	Western Michigan University
3	2014	Ohio University	Oklahoma State University
4	2015	University of Virginia	University of North Carolina at Chapel Hill

5	2016	The University of Arizona	University of South Florida
6	2016	University of California – Davis	University of Colorado Boulder
7	2016	University of California – Riverside	University of Nebraska-Lincoln
8	2017	George Mason University	University at Buffalo

I evaluated the similarity of the RCM and non-RCM matched pairs by examining the means and variances, Rubin's test, a visual examination, two-sample Kolmogorov-Smirnov test for equality of distribution functions, and chi-square tests for each matched sample for nsalary. The evaluation of matched samples by means and variances for nsalary is displayed in Table 4.33. Since the p-values are all above 0.05, I concluded that the means of the matching variables — fall graduate enrollment (*grad_pre1)*, fall undergraduate enrollment (*ug_pre1)*, Carnegie Classification (*carnegie_pre1)*, degree of urbanization (*urban_pre1)*, and change in outcome variable from RCM implementation to two years later (*outcome_dev)* — were balanced at time of matching, one year prior to RCM implementation. The variance ratio is the variance of the treated group divided by the variance of the non-treated group. Since no variable's variance ratio fell outside of the 0.20-4.99 range in the F-distribution, the matched sample for nsalary was balanced (Dettman, Giebler, & Weyh, 2019).

Table 4.33

Evaluation of Matched Samples for Average Salary Using Means and Variance Ratios

	M			t-test		
Variable	RCM	Non-RCM	%bias	*t*	*p*	Variance Ratio
grad_pre1	6623	7297	-25.500	-0.510	0.618	0.950
ug_pre1	23352	21837	30.700	0.610	0.549	1.400
carnegie_pre1	1.625	1.625	0.000	0.000	1.000	1.000
urban_pre1	17.000	15.750	16.800	0.340	0.743	1.090
outcome_dev	11.331	11.330	1.000	0.020	0.984	1.320

Note. Unbalanced samples if variance ratio outside [0.20; 4.99].

I then ran Rubin's test, which demonstrated partial evidence for the matched samples to be considered balanced. Samples were considered unbalanced if Rubin's B is greater than 25%. For nsalary, B = 57.7%, which indicated unbalanced samples. Samples were considered unbalanced if Rubin's R falls outside the range of 0.5 to 2. For nsalary, R=1, which was considered a balanced sample.

I then conducted a visual examination of the Quantile-Quantile Plots for nsalary, which are displayed in Figure 4.1. Quantile-Quantile Plots charted the degree of covariate imbalance in standardized percentage differences (StataCorp, 2017) for the matching variables (carnegie_pre, urban_pre1, grad_pre1, ug_pre1). If all dots fell on the 45-degree line, the covariate distributions for matched pairs were equal. For nsalary, there were deviations from the line for fall graduate enrollment (grad) and fall undergraduate enrollment (ug), as well for degree of urbanization (urban). The dots for the Carnegie plot all fell on the line, meaning that institutions matched exactly based on Carnegie Basic Classification. Two pairs were not well matched based on degree of urbanization (urban), and institutions were paired closely based on the dependent variable (nsalary) at time of matching (one year prior to RCM implementation).

Figure 4.1

Plots of Matched Samples for Average Salary of Assistant Professors

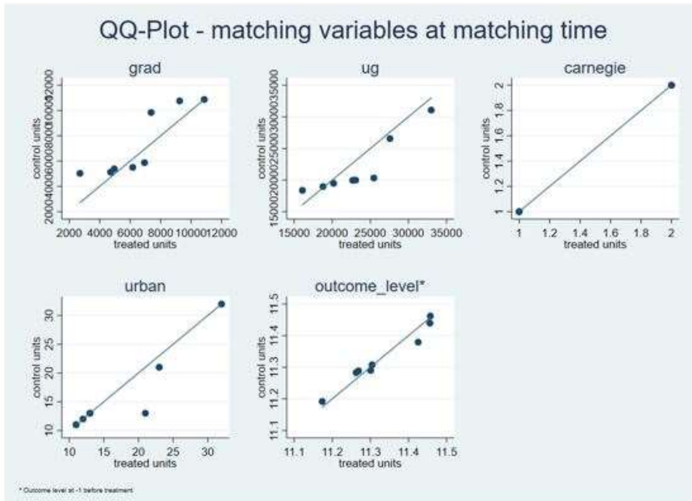

Figure 4.1. Plots of Matched Samples for Average Salary of Assistant Professors

The two-sample Kolmogorov-Smirnov tests for equality of distribution was also used to verify the matching procedure for nsalary based on statistical distance for the continuous matching variables, and the results are presented in Table 4.34. The Kolmogorov-Smirnov tests indicated no significant differences in the distributions for the matching continuous variables between the RCM and non-RCM groups. The corrected p-values for grad_pre1 (0.935), ug_pre1 (0.516), outcome_dev (0.516), and the combined test (0.935) demonstrated that the covariate distributions between RCM and non-RCM groups were not significantly different.

Table 4.34

Kolmogorov-Smirnov Evaluation of Matched Samples for Average Salary

K-smirnov	Corrected *p*
grad_pre1	0.935
ug_pre1	0.516
outcome_dev	0.516
combined	0.935
Note. Significant at $p<0.05$.	

Table 4.35 displays the results of the Chi-Square tests for distribution equality of the categorical matching variables for nsalary. The Pearson Chi-Square test statistic for carnegie_pre1 was 0.000 (p=1.000) and for urban_pre1 it was 1.200 (p=0.945), which indicated balanced samples for nsalary. In summary, the results of several evaluations of matched pairs to test for the equality of covariate distributions used for matching demonstrated that the covariate distributions used for matching were not significantly different, so I was reasonably confident that I controlled for any preexisting differences in the RCM and non-RCM groups for nsalary based on these covariates.

Table 4.35

Chi-Square Test Evaluation for Average Salary of Assistant Professors

	χ^2	*p*
carnegie_pre1	0.000	1.000
urban_pre1	1.200	0.945
Note. Significant at $p<0.05$.		

The results of four difference-in-difference approaches for RQ1 presented in Tables 4.36-4.39. From the flexible, conditional difference-in-difference estimation, I observed a smaller growth trend for logged average salary of assistant professors at RCM institutions (0.007) than their corresponding non-RCM institutions (0.017) for the period from the start of the treatment until two years afterward. There was smaller growth in salary at the RCM institutions after RCM implementation, after controlling for preexisting differences between the RCM and non-RCM universities and differences in the before and after periods for all universities. Therefore, the mean difference in the logged average salary of assistant professors at RCM and non-RCM institutions was -0.011, but the p-value of the t-tests (0.386) indicated that the difference was not significant.

Table 4.36

Flexible, Conditional Difference-in-Difference Estimation for Average Salary

		M			t-test	
Outcome	*n*	RCM	Non-RCM	Diff	*t*	*p*
nsalary	16	0.007	0.017	-0.011	0.896	0.386

Note. Significant at the *p<0.05 level.

The results from a mean treatment effect estimation within a fixed-effects difference-in-difference model for the 2-year period beginning with the year of RCM implementation are displayed in Table 4.37. To estimate the treatment effect, I used the constant and time dummy variables for the 2-year period in the flexpaneldid command. No additional covariates were included in this model. According to this model, RCM implementation had no significant effect on logged average salary of assistant professors. The coefficient of interest (postxtreat) was 0.007, indicating a small positive effect, meaning there was an additional change in salary at RCM institutions after RCM implementation, having controlled for preexisting differences between the RCM and non-RCM institutions and differences in the time before and after RCM implementation for all universities. However, the corresponding p-value of 0.712 indicated that the effect was not significant.

The results from a third difference-in-difference estimation showed a yearly, dynamic treatment effect estimation within a fixed-effects difference-in-difference model for the 2-year period beginning with the year of RCM implementation for one year and then two years following treatment are displayed in Table 4.37. To estimate the treatment effect, I used the constant and time dummy variables for the 2-year period in the flexpaneldid command. No additional covariates were included in this model. The results for a dynamic fixed effects model are also displayed in Table 4.37 and demonstrated that RCM implementation had no significant effect on logged average salary of assistant professors. The coefficient of interest for the change from implementation to one year after was 0.018, meaning there was an additional small growth in salary at RCM institutions after RCM implementation, having controlled for preexisting differences between the RCM and non-RCM institutions and differences in the time before and after RCM implementation for all universities. The coefficient of interest for the change from implementation to two years after was -0.005, meaning there was a decrease in salary at RCM institutions after RCM implementation, having controlled for preexisting differences between the RCM and non-RCM institutions and differences in the time before and after RCM implementation for all universities. However, the corresponding p-values of 0.357 and 0.809 indicated that the effects were not significant.

Table 4.37

Mean and Dynamic Fixed Effects Difference-in-Differences for Average Salary

	β	Robust *SE*	*t*	*p*	95% Conf. Interval	
Mean Fixed Effects						
postxtreat	0.007	0.018	0.380	0.712	-0.031	0.045
Dynamic Fixed Effects						
postxtreat						
Year 1	0.018	0.019	0.950	0.357	-0.022	0.058
Year 2	-0.005	0.019	-0.250	0.809	-0.044	0.035

Note. Significant at $*p<0.05$.

The results of a fourth difference-in-difference estimation for nsalary are presented in Table 4.38. I added the covariates of fall undergraduate enrollment (ug), fall graduate enrollment (grad), unionization, urbanization, and Carnegie classification to the fixed effects regression model. Fall graduate enrollment had a slightly positive, significant relationship with average salary, and urbanization had a slightly negative relationship. The coefficient for the interaction term was -0.003, meaning there was an additional negative change in salary at RCM institutions after RCM implementation, having controlled for preexisting differences between the RCM and non-RCM institutions and differences in the time before and after RCM implementation for all universities. However, the p-value was not significant (0.826), so this model also showed no significant effect of RCM implementation on average salary of assistant professors.

Table 4.38

Fixed Effects Difference-in-Difference Estimation with Covariates for Average Salary

Variable	β	SE	*t*	*p*	95% Conf. Interval	
treatxpost	-0.003	0.013	-0.220	0.826	-0.028	0.023
carnegie	-0.017	0.020	-0.850	0.398	-0.057	0.023
grad	0.000	0.000	3.490	0.001*	0.000	0.000

ug	0.000	0.000	0.640	0.527	0.000	0.000
urban	-0.007	0.002	-3.680	0.000*	-0.011	-0.003
_cons	11.235	0.108	103.670	0.000	11.020	11.450

Note. Significant at the **p*<0.05 level.

All four difference-in-difference estimations did not find any statistically significant evidence that there was a relationship between RCM implementation and average salary of assistant professors on the tenure track at public, doctoral universities between FY2011 – FY 2019.

To explore RQ1a (*average salary of assistant professors by gender*), I repeated the analysis described for RQ1 changing the dependent variables to the natural log of average salary for men (*nsalarym*) and women (*nsalaryw*) assistant professors on the tenure track equated to a 9-month contract, indexed to FY2019 values. The results of the nearest neighbor matching process for the outcome of institutional average salary of men and women assistant professors are presented in Table 4.39. The pairing of institutions differed for each nearest neighbor statistical distance matching process because the outcome variable (i.e., nsalarym) one year prior to RCM implementation for each RCM institution in the sample was included in the matching, along with the continuous and categorical institutional covariates.

Table 4.39

Matched Sample for Average Salary of Men and Women Assistant Professors

Pair	Year	RCM Institution	Non-RCM Institution	
			Men	Women
1	2012	Texas Tech University	University of Nevada-Las Vegas	University of Akron Main Campus
2	2014	Auburn University	Florida Atlantic University	Western Michigan University
3	2014	Ohio University	Oklahoma State University	Oklahoma State University

4	2015	University of Virginia	University of Kansas	University of North Carolina at Chapel Hill
5	2016	University of Arizona	University of South Florida	University of South Florida
6	2016	University of California-Davis	University of Georgia	University of Colorado-Boulder
7	2016	University of California-Riverside	University of Nebraska-Lincoln	University of Nebraska-Lincoln
8	2017	George Mason University	University at Buffalo	University at Buffalo

Note. Year equals fiscal year of RCM implementation.

I followed the same process as described for nsalary to evaluate the similarity of the matched groups for nsalarym and nsalaryw to determine the balance of variable distributions in the treated (RCM) and non-treated (non-RCM) group at the time of matching, one year before the implementation of RCM. I checked the means and variance ratios for the covariate distributions for each of the RCM and non-RCM groups for average salary of men assistant professors (nsalarym) and average salary of women assistant professors (nsalaryw). The results are displayed in Table 4.40. Since the p-values are all above 0.05, I concluded that the means of the matching variables were balanced. The variance ratio was the variance of the treated group divided by the variance of the non-treated group. Since no variable's variance ratio fell outside of the 0.20-4.99 range in the F-distribution, the matched samples for nsalarym and nsalaryw were balanced.

Table 4.40

Evaluation of Matched Sample by Means and Variance for Average Salary by Gender

	Men			Women		
Variable	*t*	*p*	Variance	*t*	*p*	Variance
grad_pre1	-0.480	0.637	1.260	-0.420	0.680	0.880
ug_pre1	0.090	0.929	1.600	0.440	0.664	1.500
carnegie_pre1	0.000	1.000	1.000	0.000	1.000	1.000
urban_pre1	0.370	0.719	1.070	0.340	0.743	1.090
outcome_dev	0.440	0.664	4.190	0.260	0.796	2.010

Note. Unbalanced samples if variance ratio outside [0.20; 4.99].

The results of Rubin's test provided partial evidence that the samples were balanced for nsalarym and nsalaryw. Rubin's B was greater than 25% for both variables, which indicated the samples were not balanced. For nsalarym, B = 60.5% and for nsalaryw, B=51.6%. However, Rubin's R indicated the samples were balanced, since Rubin's R fell within the range of 0.5 to 2, with R=1.280 for nsalarym and R=1.040 for nsalaryw.

I then conducted a visual examination of the Quantile-Quantile Plots for nsalarym and nsalaryw, which are displayed in Figure 4.2. The distributions were for fall graduate enrollment (grad) were more closely matched for nsalarym than nsalaryw. The distributions for fall undergraduate enrollment (ug) were better matched than graduate enrollment for nsalarym and nsalaryw. Institutions in the sample matched exactly by Carnegie Basic Classification (carnegie). One pair did not match well based on degree of urbanization (urban) for nsalarym and nsalaryw. There was more variation in the matched samples based on the outcome variable for nsalarym than nsalaryw at time of matching (one year prior to RCM implementation).

Figure 4.2

Plots of Matched Samples for Average Salary of Assistant Professors by Gender

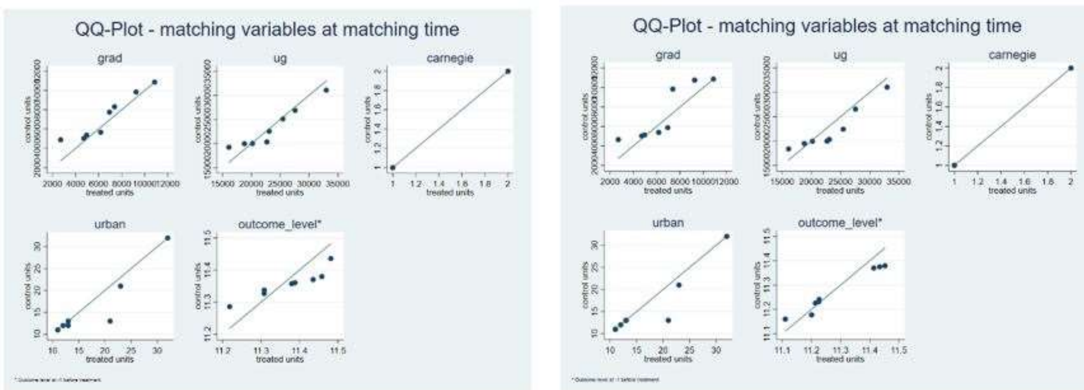

Figure 4.2. Plots of Matched Samples for Men (Left) and Women (Right) Assistant Professors

The two-sample Kolmogorov-Smirnov test for equality of distribution was used to verify the matching procedure for nsalarym and nsalaryw based on statistical distance for the continuous matching variables, and the results are presented in Table 4.41. The Kolmogorov-Smirnov tests indicated no significant differences in the covariate distributions for the matching continuous variables between the RCM and non-RCM groups. The corrected p-values for grad_pre1 (0.185), ug_pre1 (0.935), outcome_dev (0.935), and the combined test (0.185) were above 0.05, so the covariate distributions between RCM and non-RCM groups were not significantly different for nsalarym. The corrected p-values for grad_pre1 (0.516), ug_pre1 (0.935), outcome_dev (0.516), and the combined test (0.516) also demonstrated that the covariate distributions between RCM and non-RCM groups were not significantly different for nsalaryw.

Table 4.41

Kolmogorov-Smirnov Evaluation of Matched Samples for Average Salary by Gender

Variable	*p*	Variable	*p*
nsalarym		nsalaryw	
grad_pre1	0.185	grad_pre1	0.516
ug_pre1	0.935	ug_pre1	0.935
outcome_dev	0.935	outcome_dev	0.516
Combined K-S	0.185	Combined K-S	0.516

Note. *p* = Corrected p-value.

The results of the Chi-Square tests for distribution equality of the categorical matching variables for average salary of assistant professors for men (nsalarym) and women (nsalaryw) are displayed in 4.42. The Pearson Chi-Square test statistic for carnegie_pre1 was 0.000 (p=1.000) and for urban_pre1 it was 1.200 (p=0.945), which indicated balanced samples for nsalarym. The Pearson Chi-Square test statistic for carnegie_pre1 was 0.000 (p=1.000) and for urban_pre1 it was 1.200 (p=0.945), which indicated balanced samples for nsalaryw. In summary, the results of several evaluations of matched pairs to test for the equality of covariate distributions used for matching demonstrated that the covariate distributions used for matching were not significantly different, so I was reasonably confident that I controlled for any preexisting differences in the RCM and non-RCM groups for nsalarym and nsalaryw based on these covariates.

Table 4.42

Chi-Square Test Evaluation of Matched Samples for Average Salary by Gender

Variable	χ^2	*p*	Variable	χ^2	*p*
nsalarym			nsalaryw		
carnegie_pre1	0.000	1.000	carnegie_pre1	0.000	1.000
urban_pre1	1.333	0.931	urban_pre1	1.200	0.945

Note. Significant at **p*<0.05.

The results of the flexible conditional difference-in-difference estimation for nsalarym and nsalaryw are presented in Table 4.43. I observed smaller growth in the trend for logged average salary of men assistant professors at RCM institutions (0.012) compared to non-RCM institutions (0.013) and smaller growth in the trend for salary of women assistant professors at RCM institutions (0.000) than non-RCM institutions (0.010), meaning there was slower growth in salary at RCM institutions after RCM implementation, having controlled for preexisting differences between the RCM and non-RCM institutions and differences in the time before and after RCM implementation for all universities. The mean differences in the logged average salary of men and women assistant professors were -0.001 and -0.010 respectively, but the p-values of the t-tests (0.927; 0.546) indicated that these differences were not significant.

Table 4.43

Flexible, Conditional Difference-in-Difference of Average Salary by Gender

		M			t-test	
Outcome	*n*	RCM	Non-RCM	Diff	t	*p*
nsalarym	16	0.012	0.013	-0.001	0.035	0.972
nsalaryw	16	0.000	0.010	-0.010	0.619	0.546

Note. Significant at the **p*<0.05 level.

The results from a mean fixed effect difference-in-difference estimation and a yearly, dynamic treatment effect difference-in-difference estimation for the 2-year period beginning with the year of RCM implementation for average salary for men and average salary for women are displayed in Table 4.44. According to the mean fixed effects difference-in-difference estimation, RCM implementation had no significant effect on average salary of men or women. The coefficients of interest were 0.024 for men and 0.029 for women, but the corresponding p-values of 0.247 and 0.113 indicated that the effects were not significant. According to the dynamic fixed effects difference-in-difference estimation, RCM implementation did not have a significant effect on average salary of men or women assistant professors. The coefficients of interest for men were 0.031 and 0.017, but the corresponding p-values of 0.145 and 0.470 indicated that the effects were not significant. The coefficients of interest for women were -0.004 and -0.018, but the corresponding p-values of 0.850 and 0.360 indicated that the effects were not significant.

Also presented in Table 4.44 are the results of a fourth difference-in-difference estimation for nsalarym and nsalaryw. I added the covariates of fall undergraduate enrollment (ug), fall graduate enrollment (grad), unionization, urbanization, and Carnegie classification to a fixed effects regression model. Fall graduate enrollment had a slightly positive, significant relationship with average salary, and urbanization had a slightly negative relationship for both average salary of men and average salary of women. However, the model also showed no significant effect of RCM implementation on average salary of men or women assistant professors.

Table 4.44

Fixed Effects Difference-in-Difference Estimations of Average Salary by Gender

Variable	*β*	*p*	Variable	*β*	*p*
Mean Fixed Effects Model					
Men	0.024	0.247	Women	0.029	0.113
Dynamic Fixed Effects Model					
Men			Women		
Year 1	0.031	0.145	Year 1	-0.004	0.850
Year 2	0.017	0.470	Year 2	-0.018	0.360
Fixed Effects Model with Covariates					
Men			Women		
treatxpost	0.024	0.063	treatxpost	-0.013	0.361
carnegie	-0.007	0.736	carnegie	-0.040	0.068
grad	0.000	0.001*	grad	0.000	0.038*

ug	0.000	0.840	ug	0.000	0.898
urban	-0.005	0.007*	urban	-0.010	0.000*
_cons	11.271	0.000	_cons	11.405	0.000

Note. Significant at *$p<0.05$.

Based on the results of four difference-in-difference estimation models that used a nearest neighbor matching process to compare RCM and non-RCM institutions, there was no evidence that RCM implementation had a significant effect on institutional average salary of assistant professors equated to 9-month contracts at 4-year degree-granting public doctoral research universities. There was also no evidence that RCM implementation had a significant effect on institutional average salary of men or women assistant professors at these universities.

To explore RQ2 (*proportion of assistant professors on the tenure track when considering gender*), I repeated the analysis described for RQ1a changing the dependent variables to the proportion of men (*pmen*) and women (*pwomen*) assistant professors on the tenure track. The results of the nearest neighbor matching process for the outcome of proportions of men and women assistant professors are displayed in Table 4.45. Because pmen and pwomen are directly dependent on one another, the pairing of institutions based on proportion of men assistant professors one year prior to RCM implementation was the same as the pairing of institutions based on the proportion of women assistant professors.

Table 4.45

Matched Sample for Proportions of Men and Women Assistant Professors

Pair	Year	RCM Institution	Non-RCM Institution	
			Men	Women
1	2012	Texas Tech University	University of Nevada-Las Vegas	University of Nevada-Las Vegas
2	2014	Auburn University	Northern Arizona University	Northern Arizona University
3	2014	Ohio University	Louisiana Tech University	Louisiana Tech University

4	2015	University of Virginia	University of Kansas	University of Kansas
5	2016	University of Arizona	University of South Florida	University of South Florida
6	2016	University of California-Davis	Colorado State University-Fort Collins	Colorado State University-Fort Collins
7	2016	University of California-Riverside	University of California-San Diego	University of California-San Diego
8	2017	George Mason University	University at Buffalo	University at Buffalo

Note. Year equals Fiscal Year of RCM implementation.

To evaluate the similarity of the matched groups for pmen and pwomen, I checked the means and variances for the covariate distributions for each of the RCM and non-RCM groups for proportion of men assistant professors (pmen) and women assistant professors (pwomen). The results are displayed in Table 4.46. Since the p-values are all above 0.05, I concluded that the means of the matching variables grad_pre1, ug_pre1, carnegie_pre1, urban_pre1, and outcome_dev were balanced for pmen and pwomen. The variance ratio was the variance of the treated group divided by the variance of the non-treated group. Since no variable's variance ratio fell outside of the 0.20-4.99 range in the F-distribution, the matched samples for pmen and pwomen were balanced.

Table 4.46

Evaluation of Matching for Gender Proportions Using Means and Variance Ratios

	pmen			pwomen		
Variable	*t*	*p*	Variance	*t*	*p*	Variance
grad_pre1	-0.130	0.902	0.840	-0.130	0.902	0.840
ug_pre1	0.640	0.531	0.730	0.640	0.531	0.730
carnegie_pre1	0.000	1.000	1.000	0.000	1.000	1.000
urban_pre1	0.370	0.719	1.070	0.370	0.719	1.070
outcome_dev	-0.210	0.835	0.660	0.210	0.835	0.660

Note. Unbalanced samples if variance ratio outside [0.20; 4.99].

The results of Rubin's test provided evidence that the samples were unbalanced for pmen and pwomen. Rubin's B was greater than 25% for both variables, which indicated the samples were not balanced. For pmen, B = 61.0% and for pwomen, B=61.0%. Rubin's R also indicated the samples were unbalanced, since Rubin's R did not fall within the range of 0.5 to 2, with R=5.95 for both pmen and pwomen.

I then conducted a visual examination of the Quantile-Quantile Plots for the proportion of men (pmen) and women (pwomen) assistant professors, which are displayed in Figure 4.3. The covariate distributions were closely matched for fall graduate enrollment (grad) and fall undergraduate enrollment (ug) was well matched except for one outlier for pmen and pwomen. Institutions in the sample matched exactly by Carnegie Basic Classification (carnegie). One pair did not match well based on degree of urbanization (urban) for each gender proportion. There was moderate, similar variation in the distribution for the outcome variables for both pmen and pwomen at time of matching (one year prior to RCM implementation).

Figure 4.3

Plots for Matched Sample of Proportion of Assistant Professors by Gender

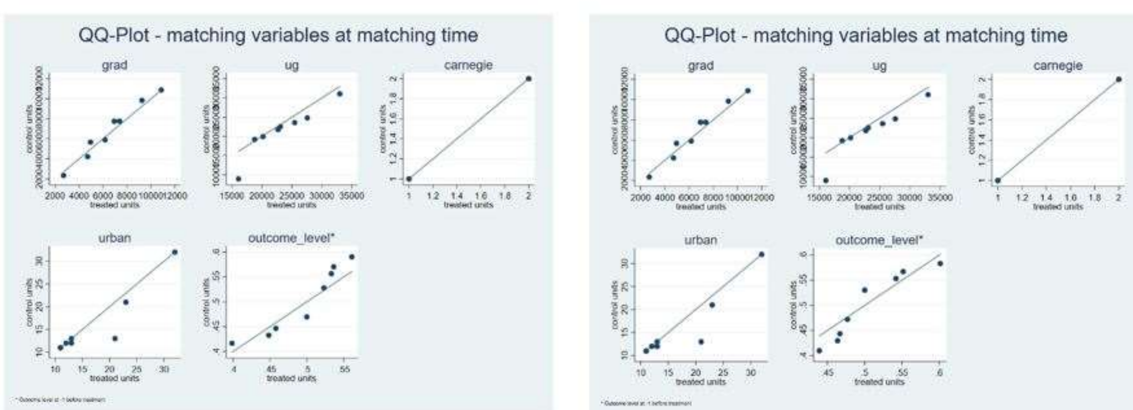

Figure 4.3. Plots for Matched Sample of Proportion of Men (Left) and Women (Right)

The Kolmogorov-Smirnov tests for equality of distribution indicated no significant differences in the distributions for the matching continuous variables between the RCM and non-RCM groups. The results are presented in Table 4.47. The corrected p-value was 0.935 for the covariates for pmen and pwomen so the covariate distributions between RCM and non-RCM groups were not significantly different for either outcome.

Table 4.47

Kolmogorov-Smirnov Evaluation of Matched Samples for Gender Proportions

Variable	*p*	Variable	*p*
pmen		pwomen	
grad_pre1	0.935	grad_pre1	0.935
ug_pre1	0.935	ug_pre1	0.935
outcome_dev	0.935	outcome_dev	0.935
Combined K-S	0.935	Combined K-S	0.935

Note. Corrected p-value = *p*.

Table 4.48 displays the results of the Chi-Square tests for distribution equality of the categorical matching variables for proportion of men assistant professors (pmen) and women (pwomen). The Pearson Chi-Square test statistic for carnegie_pre1 was 0.000 (p=1.000) and for urban_pre1 it was 1.333 (p=0.931) for both pmen and pwomen, which indicated balanced samples for both outcomes. In summary, the results of the majority of evaluations of matched pairs demonstrated that the covariate distributions used for matching were not significantly different, so I was reasonably confident that there were not preexisting differences in the RCM and non-RCM groups for pmen and pwomen based on these covariates.

Table 4.48

Chi-Square Test Evaluation of Matched Samples for Gender Proportions

Variable	χ^2	*p*	Variable	χ^2	*p*
pmen			pwomen		
carnegie_pre1	0.000	1.000	carnegie_pre1	0.000	1.000
urban_pre1	1.333	0.931	urban_pre1	1.333	0.931

Note. Significant at $^*p<0.05$.

The results of a flexible conditional difference-in-difference estimation for the individual differences of the gender proportions of assistant professors between RCM and non-RCM institutions are displayed in Table 4.49. I observed a small, negative difference in the trend for the mean proportion of men assistant professors for the period from the start of the treatment until two years afterward, for RCM institutions (0.001) and their corresponding non-RCM institutions (0.041), meaning the proportion of men increased at a slower rate at RCM universities than at non-RCM institutions after controlling for preexisting differences between RCM and non-RCM universities and differences in the before and after RCM implementation periods for all universities. The mean difference in the proportion of men assistant professors at RCM and non-RCM institutions was -0.040, but the p-value of the t-test (0.220) indicated that this difference was not significant.

As expected due to its inverse relationship with mean proportion of men assistant professors, I observed a small, positive difference in the trend for the mean proportion of women assistant professors for the period from the start of the treatment until two years afterward, for RCM universities (-0.001) and their corresponding non-RCM universities (-0.041), meaning the proportion of women decreased at a slower rate at RCM universities than at non-RCM institutions after controlling for preexisting differences between RCM and non-RCM universities and differences in the before and after RCM implementation periods for all universities. The mean difference in the proportion of women assistant professors at RCM and non-RCM institutions was 0.040, but the p-value of the t-test (0.220) indicated that this difference was also not significant.

Table 4.49

Flexible, Conditional Difference-in-Difference for Assistant Professors by Gender

		M			t-test	
Outcome	*N*	RCM	Non-RCM	Diff	*t*	*p*
pmen	16	0.001	0.041	-0.040	1.284	0.220
pwomen	16	-0.001	-0.041	0.040	-1.284	0.220

Note. Significant at the $*p<0.05$ level.

The results from a mean fixed effect difference-in-difference estimation and a yearly, dynamic treatment effect difference-in-difference estimation for the 2-year period beginning with the year of RCM implementation for proportion of men assistant professors (pmen) and proportion of women assistant professors (pwomen) are displayed in Table 4.50. According to the mean fixed effects difference-in-difference estimation, RCM implementation had no significant effect on proportion of men or women. The coefficients of interest were -0.017 for men and 0.017 for women, but the corresponding p-values of 0.060 and 0.403, respectively, indicated that the effects were not significant. According to the dynamic fixed effects difference-in-difference estimation, RCM implementation had no significant effect on proportion of men or women. The coefficients of interest for proportion of men were -0.017 and -0.017, but the corresponding p-values of 0.431 and 0.401 indicated that the effects were not significant. The coefficients of interest for proportion of women were 0.017 and 0.017, but the corresponding p-values of 0.431 and 0.401 indicated that the effects were not significant.

The results of a fourth difference-in-difference estimation for pmen and pwomen are also presented in Table 4.50. I added the covariates of fall undergraduate enrollment (ug), fall graduate enrollment (grad), unionization, urbanization, and Carnegie classification to the fixed effects regression model. This model also showed no significant effect of RCM implementation on proportion of men or women assistant professors.

Table 4.50

Fixed Effects Difference-in-Difference for Gender Proportions of Assistant Professors

Variable	β	p	Variable	β	p
Mean Fixed Effects Model					
pmen	-0.017	0.060	pwomen	0.017	0.403
Dynamic Fixed Effects Model					
pmen			pwomen		
Year 1	-0.017	0.431	Year 1	0.017	0.431
Year 2	-0.017	0.401	Year 2	0.017	0.401
Fixed Effects Model with Covariates					
pmen			pwomen		
treatxpost	-0.007	0.601	treatxpost	0.007	0.601
carnegie	-0.008	0.562	carnegie	0.008	0.562
grad	0.000	0.009*	grad	0.000	0.009*
ug	0.000	0.182	ug	0.000	0.182
urban	-0.001	0.722	urban	0.001	0.722
_cons	0.321	0.003	_cons	0.679	0.000

Note. Significant at $*p<0.05$.

Based on the results of four difference-in-difference estimation models that used a nearest neighbor matching process to compare RCM and non-RCM institutions, there was no evidence that RCM implementation had a significant effect on institutional proportions of men or women assistant professors on the tenure track equated to 9-month contracts at 4-year degree-granting public doctoral research universities.

To explore RQ2a (*proportion of assistant professors on the tenure track when considering gender and race/ethnicity*), I repeated the analysis described for RQ2 changing the dependent variable to the proportions of men and women by race/ethnicity for assistant professors on the tenure track. The results of the evaluation of the nearest neighbor matching process and difference-in-difference estimation for RQ2a are presented in Tables 4.51 – 4.60. The results of the nearest neighbor matching process for men assistant professors by race/ethnicity and RCM implementation are presented in Table 4.51 and the results of the nearest neighbor matching process for women assistant professors by race/ethnicity and RCM implementation are presented in Table 4.52. RCM institutions were listed in the top row with the institutional match from the control group in the row that corresponds with the assistant professor proportion for which they were matched. The pairing of institutions based on proportions of assistant professors by race/ethnicity differed based on the inclusion of the proportion outcome variables.

Table 4.51

Matched Samples of Institutions for Proportions of Men by Race and RCM

	RCM Institutions			
Proportion	Texas Tech University (2012)	Auburn University (2014)	Ohio University (2014)	University of Virginia (2015)
pasianm	University of Nevada-Las Vegas	Northern Arizona University	University of South Dakota	University of Kansas
pblackm	University of Nevada-Las Vegas	Florida Atlantic University	Louisiana Tech University	University of Kansas
phispm	University of Nevada-Las Vegas	Florida Atlantic University	Louisiana Tech University	University of Kansas
pnativem	University of Nevada-Las Vegas	Northern Arizona University	Louisiana Tech University	University of Kansas
pnonresm	University of North Texas	Western Michigan University	Louisiana Tech University	University of Kansas
ptwom	University of Nevada-Las Vegas	Western Michigan University	Louisiana Tech University	University of Kansas
punkm	University of Nevada-Las Vegas	Florida Atlantic University	University of South Dakota	University of Kansas

pwhitem	University of Nevada-Las Vegas	Southern Illinois University-Carbondale	Louisiana Tech University	University of Kansas

	RCM Institutions			
Proportion	University of Arizona (2016)	University of California – Davis (2016)	University of California – Riverside (2016)	George Mason University (2017)
pasianm	University of Houston	Georgia State University	University of California-San Diego	University of Maryland-College Park
pblackm	University of Houston	Georgia State University	University of Nebraska-Lincoln	University of Maryland-College Park
phispm	North Carolina State University at Raleigh	Georgia State University	University of Nebraska-Lincoln	University at Buffalo
pnativem	University of Houston	Georgia State University	University of Nebraska-Lincoln	University of Connecticut
pnonresm	University of South Florida	Georgia State University	University of New Mexico	University at Buffalo
ptwom	North Carolina State University at Raleigh	University of Georgia	University of New Mexico	University of Maryland-College Park
punkm	University of Houston	Georgia State University	University of Nebraska-Lincoln	University of Maryland-College Park
pwhitem	University of Houston	Georgia State University	University of Nebraska-Lincoln	University at Buffalo

Note. (Year) = Fiscal Year of RCM implementation.

Table 4.52

Matched Samples of Institutions for Proportions of Women by Race and RCM

	RCM Institutions			
Proportion	Texas Tech University (2012)	Auburn University (2014)	Ohio University (2014)	University of Virginia (2015)
pasianw	University of Nevada-Las Vegas	Florida Atlantic University	Louisiana Tech University	SUNY at Albany
pblackw	University of Nevada-Las Vegas	Western Michigan University	Louisiana Tech University	University of Kansas
phaww	University of Nevada-Las Vegas	Western Michigan University	Louisiana Tech University	University of Kansas
phispw	University of Nevada-Las Vegas	Florida Atlantic University	University of South Dakota	University of Kansas
pnativew	University of North Texas	Western Michigan University	Louisiana Tech University	University of Kansas
pnonresw	University of Nevada-Las Vegas	Northern Arizona University	Louisiana Tech University	University of Kansas
ptwow	University of Nevada-Las Vegas	Western Michigan University	Louisiana Tech University	University of Kansas

punkw	University of Nevada-Las Vegas	Northern Arizona University	University of South Dakota	University of Kansas
pwhitew	University of Nevada-Las Vegas	Western Michigan University	Louisiana Tech University	University of North Carolina-Chapel Hill

	RCM Institutions			
Proportion	University of Arizona (2016)	University of California – Davis (2016)	University of California – Riverside (2016)	George Mason University (2017)
pasianw	University of Houston	Georgia State University	University of Nebraska-Lincoln	University of Maryland-College Park
pblackw	University of Houston	Georgia State University	University of Nebraska-Lincoln	University of Maryland-College Park
phaww	University of Houston	Georgia State University	University of Nebraska-Lincoln	University of Maryland-College Park
phispw	University of Houston	University of Georgia	University of Nebraska-Lincoln	University of Connecticut
pnativew	University of Houston	Georgia State University	University of Hawaii at Manoa	University of Maryland-College Park
pnonresw	North Carolina State University at Raleigh	Georgia State University	University of New Mexico	University at Buffalo
ptwow	University of Houston	University of Georgia	University of Nebraska-Lincoln	University at Buffalo
punkw	University of Houston	Georgia State University	University of Nebraska-Lincoln	University of Maryland-College Park
pwhitew	University of Houston	Georgia State University	University of New Mexico	University at Buffalo

Note. (Year) = Fiscal Year of RCM implementation.

To evaluate the similarity of the matched groups for proportions of Asian, Black or African American, Native Hawaiian or Other Pacific Islander, Hispanic or Latino, American Indian or Alaskan Native, Nonresident Alien, Two or More Races, Race/Ethnicity Unknown, and White men and women assistant professors, I checked the means and variances for the covariate distributions for each of the RCM and non-RCM groups. The results are displayed in Table 4.53. Because the all pairs matched exactly based on Carnegie Classification, each mean had a p-value of 1.000 and a variance ratio of 1.000 and were not included in Table 4.53. For the other covariates, the p-values for the means were all above 0.05. Therefore, I concluded that the means of the matching variables were balanced for all proportions. I removed the _pre1 suffix (represented one year prior to RCM implementation and time of matching) from the matching variables in Table 4.53 for readability.

The variance ratio fell outside of the recommended 0.20-4.99 range for Latina women assistant professors, which provided evidence that those matched samples were unbalanced. The variance ratio for Native Hawaiian or Other Pacific Islander and Hispanic women assistant professors was missing because there were no women assistant professors in the treatment or control group prior to RCM implementation in this sample. Since no other variable's variance ratio falls outside of the 0.20-4.99 range in the F-distribution, the matched samples for all other gender and race/ethnicity proportions were balanced. Given the large number of comparisons I would expect approximately 5% of the comparisons to be different due to random chance with a p-value of 0.05.

Table 4.53

Evaluation of Matching for Proportions Using Means and Variance Ratios

	Men			Women		
Variable	*t*	*p*	Variance	*t*	*p*	Variance
Asian (pasian)						
Grad	0.100	0.919	1.100	0.460	0.652	1.060
Ug	0.190	0.849	0.530	0.430	0.672	0.460
Urban	0.400	0.696	1.050	0.400	0.696	1.050
Outcome	-0.050	0.959	0.970	0.360	0.722	0.650
Black or African American (pblack)						
Grad	0.150	0.885	1.070	0.130	0.902	1.090
Ug	0.210	0.838	0.570	0.430	0.672	0.570
Urban	0.400	0.696	1.050	0.400	0.696	1.050
Outcome	-0.000	0.999	0.410	1.620	0.127	3.330
Native Hawaiian or Other Pacific Islander (phaw)						
Grad	-	-	-	0.130	0.902	1.090
Ug	-	-	-	0.430	0.672	0.570
Urban	-	-	-	0.400	0.696	1.050

	Men			Women		
Variable	*t*	*p*	Variance	*t*	*p*	Variance
Outcome	-	-	-	1.000	0.334	.*
Hispanic or Latino (phisp)						
Grad	0.070	0.945	1.050	0.280	0.782	1.580
Ug	1.000	0.336	1.000	0.530	0.607	0.520
Urban	0.400	0.696	1.050	0.370	0.719	1.070
Outcome	0.580	0.571	1.060	2.320	0.036	6.420*
American Indian or Alaskan Native (pnative)						
Grad	0.490	0.630	1.550	-0.140	0.893	1.090
Ug	0.700	0.493	0.620	0.400	0.694	0.440
Urban	0.400	0.696	1.050	0.400	0.696	1.050
Outcome	0.770	0.456	2.670	1.220	0.241	1.820
Nonresident Alien (pnonres)						
Grad	-0.400	0.697	0.940	0.040	0.972	1.040
Ug	0.520	0.610	0.620	1.090	0.293	1.100
Urban	0.400	0.696	1.050	0.400	0.696	1.050
Outcome	0.100	0.922	0.890	0.480	0.639	1.110
Two or More Races (ptwo)						
Grad	-0.230	0.818	0.950	0.100	0.918	1.190
Ug	0.720	0.486	0.830	0.680	0.508	0.600
Urban	0.370	0.719	1.070	0.370	0.719	1.070
Outcome	0.790	0.444	3.420	0.450	0.661	0.850
Race/Ethnicity Unknown (punk)						
Grad	0.120	0.903	1.120	0.190	0.854	1.060
Ug	0.250	0.806	0.520	0.380	0.708	0.530
Urban	0.400	0.696	1.050	0.400	0.696	1.050
Outcome	-0.280	0.782	0.700	0.290	0.777	1.600
White (pwhite)						
Grad	0.260	0.802	1.240	-0.180	0.860	0.940
Ug	0.940	0.365	0.550	0.710	0.488	0.620
Urban	0.400	0.696	1.050	0.400	0.696	1.050
Outcome	-0.070	0.948	2.410	0.360	0.721	3.020

Note. Unbalanced samples if variance ratio outside [0.20; 4.99]. Analysis was not conducted for phawm as there were no Native Hawaiian or Other Pacific Islander men at RCM institutions in this sample.

The results of Rubin's test are provided in Table 4.54. The results provide evidence that the samples were unbalanced for almost all the gender and race/ethnicity proportions for assistant professors. Rubin's B was greater than 25% for all variables, which indicated the samples were not balanced. Rubin's R also indicated the samples were unbalanced, since Rubin's R did not fall within the range of 0.5 to 2 for all other outcome variables, with the exceptions of punkm, (R=0.86) and pwhitem (R=1.91),

Table 4.54

Rubin's Test Evaluation of Matched Samples for Gender and Race Proportions

Variable	B	R	Variable	B	R
pasianm	32.3%*	3.59*	pasianw	52.8%*	2.67*
plackm	27.6%*	3.23*	plackw	100.2%*	2.22*
phawm	-	-	phaww	56.8%*	2.04*
phispm	74.5%*	10.47*	phispw	131.3%*	6.13*
pnativem	79.9%*	2.69*	pnativew	98.0%*	3.70*
pnonresm	86.7%*	2.65*	pnonresw	121.0%*	3.05*
ptwom	75.2%*	8.36*	ptwow	67.1%*	2.04*
punkm	40.0%*	0.86	punkw	35.0%*	2.64*
pwhitem	71.2%*	1.91	pwhitew	67.1%*	5.27*

Note. If Rubin's B>25%*, samples are unbalanced. If Rubin's R outside [0.5; 2]*, samples are unbalanced. Analysis was not conducted for phawm as there were no Native Hawaiian or Other Pacific Islander men at RCM institutions in this sample.

I then conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of Asian men and proportion of Asian women, which are displayed in Figure 4.4. For pasianm, the distributions for fall graduate enrollment (grad) were closely matched and fall undergraduate enrollment (ug) had one outlier. For pasianw, the distributions for fall graduate enrollment (grad) were more loosely matched and fall undergraduate enrollment (ug) had two outliers. Both proportions matched exactly on Carnegie Basic Classification (carnegie) and each proportion had one pair that did not match well based on degree of urbanization (urban). There was more variation in the dependent variable distribution for pasianw than pasianm.

Figure 4.4

Plots of Matched Samples for Proportion of Asian Men and Asian Women

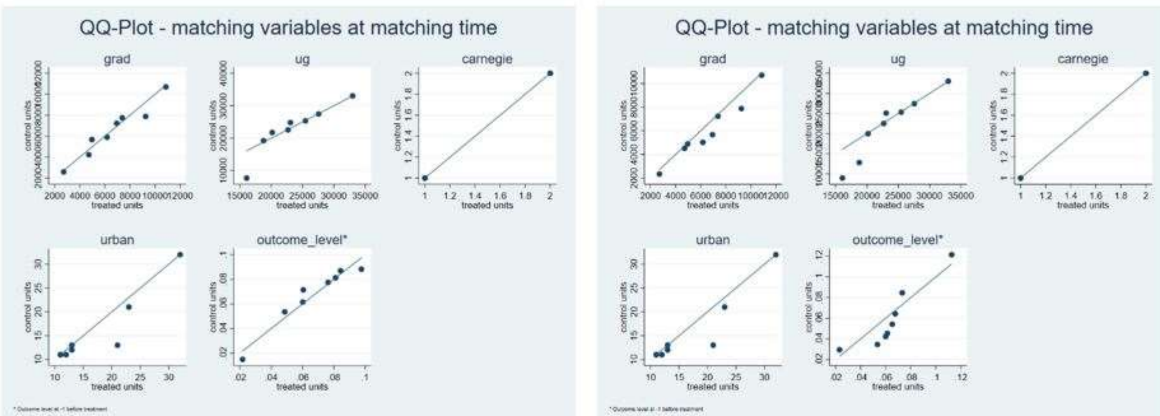

Figure 4.4. Plots of Matched Samples for Proportion of Asian Men (Left) and Women (Right)

I conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of Black men and proportion of Black women, which are displayed in Figure 4.5. The distributions for each proportion were closely matched with one pair slightly apart for fall graduate enrollment (grad) and one outlier for fall undergraduate enrollment (ug). The covariate distributions for Carnegie Basic Classification (carnegie) matched exactly and only one pair did not match on degree of urbanization (urban) for each proportion. The dependent variable distribution for Black men (pblackm) was well matched, but the distribution for proportion of Black women (pblackw) had marked variation at time of matching, one year prior to RCM implementation.

Figure 4.5

Plots of Matched Samples for Proportion of Black Men and Black Women

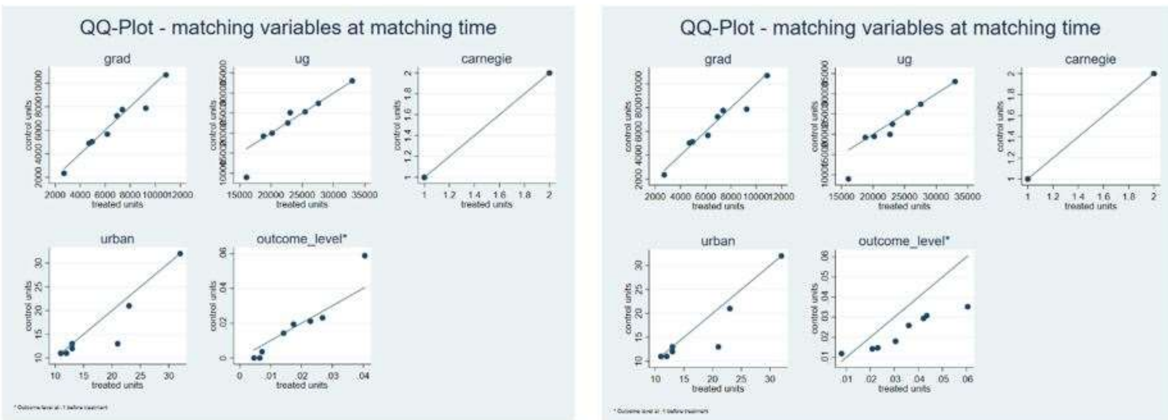

Figure 4.5. Plots of Matched Samples for Proportion of Black Men (Left) and Women (Right)

I then conducted a visual examination of the Quantile-Quantile Plots for the proportion of Hawaiian women assistant professors (phaww), which are displayed in Figure 4.6. The covariate distributions were closely matched for fall graduate enrollment (grad) with one slight outlier. Fall undergraduate enrollment (ug) was closely matched with one strong outlier. Institutions in the sample matched exactly by Carnegie Basic Classification (carnegie). One pair did not match well based on degree of urbanization (urban) and one pair did not match well on the dependent variable, proportion of Hawaiian women assistant professors (phaww) at time of matching (one year prior to RCM implementation).

Figure 4.6

Plots for Matched Sample of Proportion of Hawaiian Women Assistant Professors

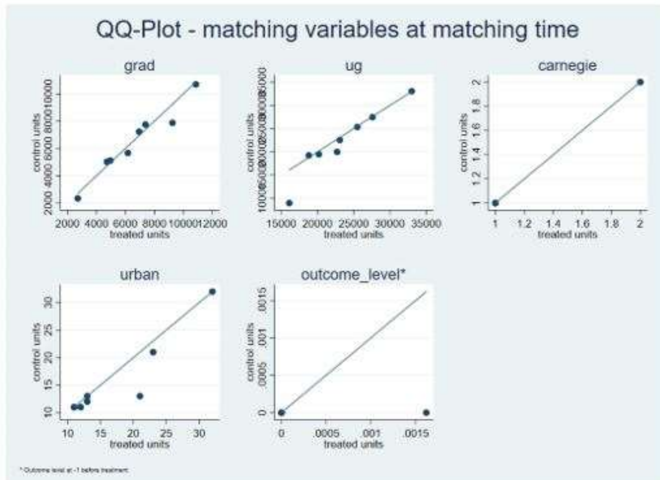

Figure 4.6. Plots for Matched Sample of Proportion of Hawaiian Women Assistant Professors

I conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of Hispanic or Latino men (phispm) and proportion of Hispanic or Latina women (phispw), which are displayed in Figure 4.7. The covariate distribution for phispm was closely matched for fall graduate enrollment (grad) with slightly more variation for phispw. There were two outlier pairs for fall undergraduate enrollment (ug) for phispm and only one outlier for phispw. The covariate distributions for Carnegie Basic Classification (carnegie) matched exactly and only one pair was not well matched on degree of urbanization (urban) for each proportion. The outcome distribution for phispm was reasonably matched, but the outcome distribution for phispw was poorly matched one year prior to RCM implementation.

Figure 4.7

Plots of Matched Samples for Proportion of Hispanic or Latino Men and Women

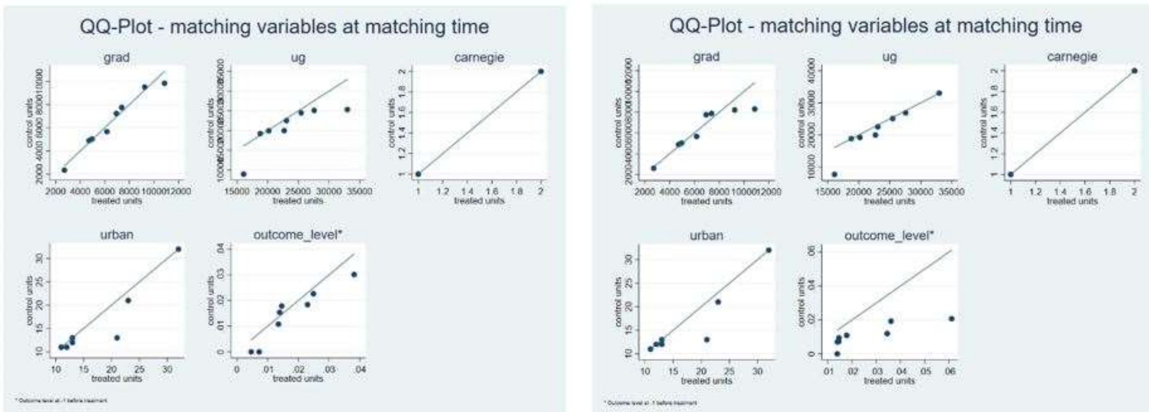

Figure 4.7. Plots of Matched Samples for Hispanic or Latino Men (Left) and Women (Right)

I conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of American Indian or Native Alaskan men (pnativem) and proportion of American Indian or Native Alaskan women (pnativew), which are displayed in Figure 4.8. The covariate distribution for fall graduate enrollment (grad) was a slightly closer match for pnativem than pnativew. There were two outlier pairs for fall undergraduate enrollment (ug) for pnativew and only one outlier for pnativem. The covariate distributions for Carnegie Basic Classification (carnegie) matched exactly and one pair was not well matched on degree of urbanization (urban) for each proportion. The outcome distribution for pnativem had a clear outlier and the outcome distribution for pnativew was poorly matched one year prior to RCM implementation.

Figure 4.8

Plots of Matched Samples for Proportion of American Indian Men and Women

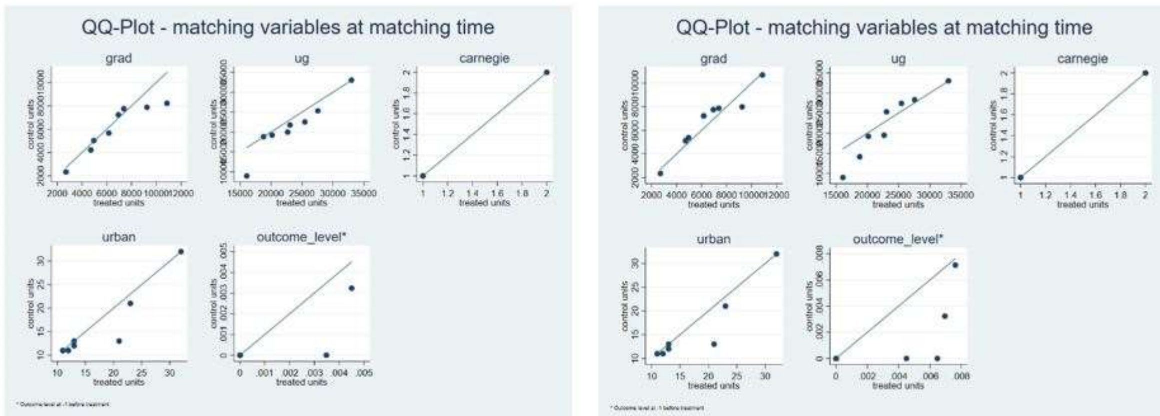

Figure 4.8. Plots of Matched Samples for American Indian Men (Left) and Women (Right)

I conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of Nonresident Alien men (pnonresm) and proportion of Nonresident Alien women (pnonresw), which are displayed in Figure 4.9. The covariate distribution for fall graduate enrollment (grad) were well matched for pnonresm and pnonresw. There were two outlier pairs for fall undergraduate enrollment (ug) for pnonresw and only one outlier for pnonresm. The covariate distributions for Carnegie Basic Classification (carnegie) matched exactly and one pair was not well matched on degree of urbanization (urban) for each proportion. The outcome distribution for pnonresm was well matched and better matched than the outcome distribution for pnonresw one year prior to RCM implementation.

Figure 4.9

Plots of Matched Samples for Proportion of Nonresident Alien Men and Women

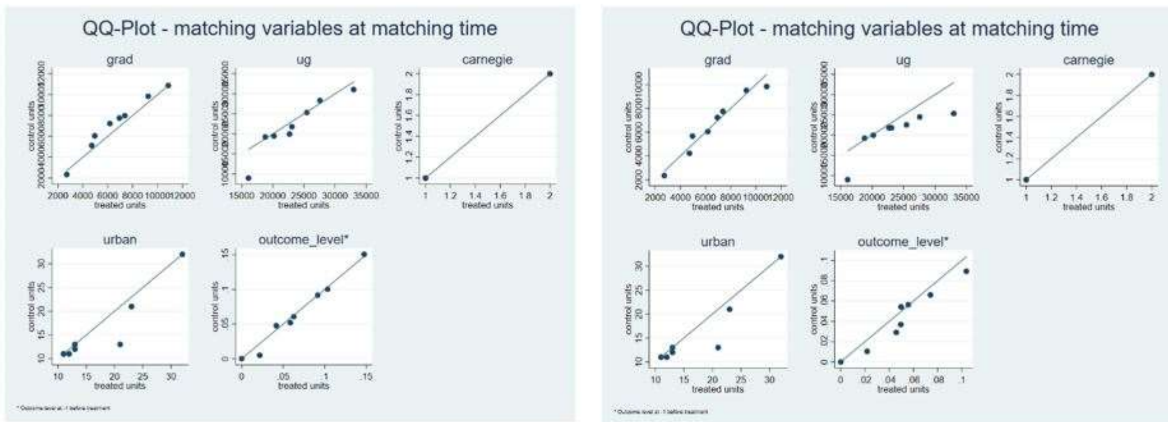

Figure 4.9. Plots of Matched Samples for Nonresident Alien Men (Left) and Women (Right)

I conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of Two or More Races men (ptwom) and proportion of Two or More Races women (ptwow), which are displayed in Figure 4.10. The covariate distribution for fall graduate enrollment (grad) were fairly well matched for ptwom and ptwow. There were two outlier pairs for fall undergraduate enrollment (ug) for ptwom and one outlier for ptwow. The covariate distributions for Carnegie Basic Classification (carnegie) matched exactly and one pair was not well matched on degree of urbanization (urban) for each proportion. The outcome distributions for ptwom and ptwow were not well matched for most institutional pairs one year prior to RCM implementation.

Figure 4.10

Plots of Matched Samples for Proportion of Two or More Races Men and Women

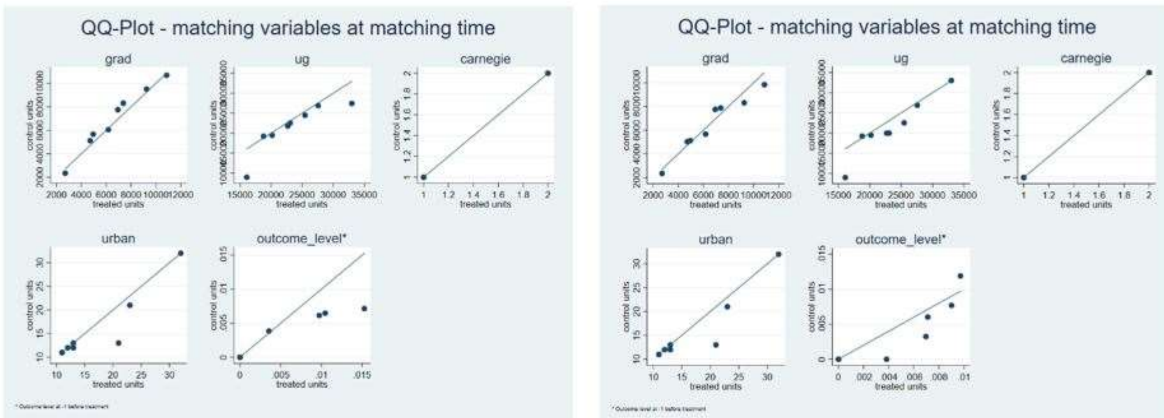

Figure 4.10. Plots of Matched Samples for Two or More Races Men (Left) and Women (Right)

I conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of Race/Ethnicity Unknown men (punkm) and proportion of Race/Ethnicity Unknown women (punkw), which are displayed in Figure 4.11. The covariate distributions for fall graduate enrollment (grad) were well matched for punkm and punkw. There was one outlier each for fall undergraduate enrollment (ug) for punkm and punkw. The covariate distributions for Carnegie Basic Classification (carnegie) matched exactly and one pair was not well matched on degree of urbanization (urban) for each proportion. The outcome distributions for punkm and punkw each out two outliers.

Figure 4.11

Plots of Matched Samples for Proportion of Race/Ethnicity Unknown Men and Women

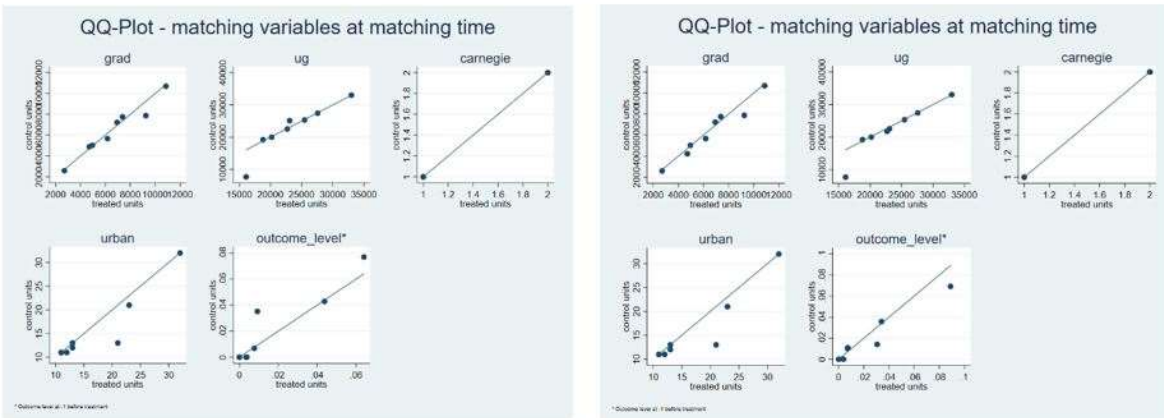

Figure 4.11. Plots for Race/Ethnicity Unknown Men (Left) and Women (Right)

I conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of White men (pwhitem) and proportion of White women (pwhitew), which are displayed in Figure 4.12. The covariate distributions for fall graduate enrollment (grad) were well matched for pwhitem and pwhitew. The covariate distributions for fall undergraduate enrollment (ug) were not as well matched and pwhitem had two outliers and pwhitew had one outlier. The covariate distributions for Carnegie Basic Classification (carnegie) matched exactly and one pair was not well matched on degree of urbanization (urban) for each proportion. The outcome distributions for pwhitem were fairly well matched with two outliers and the outcome distributions for pwhitew were well matched with one outlier.

Figure 4.12

Plots of Matched Samples for Proportion of White Men and Women

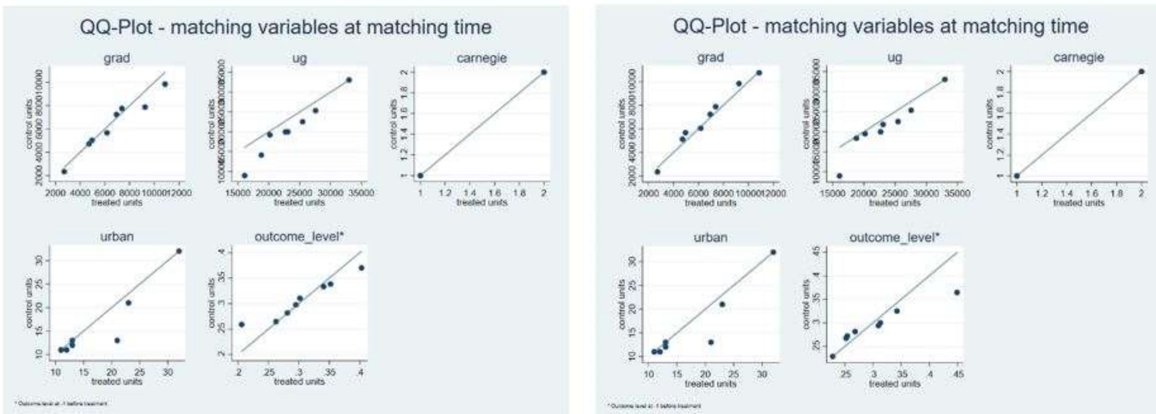

Figure 4.12. Plots of Matched Samples for Proportion of White Men (Left) and Women (Right)

The results of the Kolmogorov-Smirnov tests for equality of distribution are presented in Table 4.55. The Kolmogorov-Smirnov tests indicated no significant differences in the covariate distributions for the matched sample continuous variables between the RCM and non-RCM groups since all corrected p-values were above 0.05.

Table 4.55

Kolmogorov-Smirnov Evaluation of Matching for Gender and Race Proportions

Variable	grad_pre1	ug_pre1	outcome_dev	Combined K-S
pasianm	0.935	1.000	1.000	0.935
pblackm	0.516	1.000	1.000	0.516
phispm	0.935	1.000	0.516	0.935
pnativem	0.935	0.935	0.516	0.935
pnonresm	1.000	0.935	0.935	1.000
ptwom	0.516	0.935	0.935	0.516
punkm	0.935	1.000	1.000	0.935
pwhitem	0.935	1.000	0.516	0.935
pasianw	0.516	0.935	0.935	0.516

Variable	grad_pre1	ug_pre1	outcome_dev	Combined K-S
pblackw	0.185	0.935	0.935	0.185
phaww	1.000	0.935	0.935	1.000
phispw	0.011	0.935	0.935	0.011
pnativew	0.516	0.935	0.935	0.516
pnonresw	0.935	1.000	0.516	0.935
ptwow	0.935	0.935	0.516	0.935
punkw	0.935	1.000	0.935	0.935
pwhitew	0.935	0.935	0.516	0.935

Note. Numbers displayed are corrected p-values. Significant at $*p < 0.05$.

Table 4.56 displays the results of the Chi-Square tests for distribution equality of the categorical matching variables for proportion of men and women assistant professors by race/ethnicity for the categorical matching variables, Carnegie Basic Classification (carnegie_pre1) and Degree of Urbanization (urban_pre1). The _pre1 suffix has been removed from the table for readability. A significant p-value (less than 0.05) indicates the samples are not balanced. The Pearson Chi-Square test statistics for carnegie_pre1 and urban_pre1 were not significant, which indicated balanced matched samples for all gender and race/ethnicity proportions. In summary, a majority of the evaluations of matched pairs demonstrated that the covariate distributions used for matching were not significantly different, so I was somewhat confident that there were not significant preexisting differences in the RCM and non-RCM groups for pmen and pwomen based on these covariates.

Table 4.56

Chi-Square Evaluation of Matched Samples for Gender and Race Proportions

	carnegie		urban			carnegie		urban	
Variable	χ^2	*p*	χ^2	*p*	Variable	χ^2	*p*	χ^2	*p*
pasianm	0.000	1.000	1.200	0.945	pasianw	0.000	1.000	1.200	0.945
pblackm	0.000	1.000	1.200	0.945	pblackw	0.000	1.000	1.200	0.945
phawm	-	-	-	-	phaww	0.000	1.000	1.200	0.945
phispm	0.000	1.000	1.200	0.945	phispw	0.000	1.000	1.333	0.931
pnativem	0.000	1.000	1.200	0.945	pnativew	0.000	1.000	1.200	0.945
pnonresm	0.000	1.000	1.200	0.945	pnonresw	0.000	1.000	1.200	0.945
ptwom	0.000	1.000	1.333	0.931	ptwow	0.000	1.000	1.333	0.931
punkm	0.000	1.000	1.200	0.945	punkw	0.000	1.000	1.200	0.945
pwhitem	0.000	1.000	1.200	0.945	pwhitew	0.000	1.000	1.200	0.945

Note. Significant at *$p < 0.05$. Analysis was not conducted for phawm as there were no Native Hawaiian or Other Pacific Islander men at RCM institutions in this sample.

In summary, the combination of tests that evaluated the covariate distributions for institutional matched pairs one year prior to RCM implementation demonstrated that there not significant differences between RCM and non-RCM groups. The evaluation of means, variance ratios, K-S test, and Chi-square tests did not offer evidence of significant differences between RCM and non-RCM groups. Rubin's B, Rubin's R, and a visual examination of covariate distributions did provide evidence that the outcomes were not well matched for American Indian or Native Alaskan and Two or More Races men and women, as well as Black or African American Women, Native Hawaiian or Other Pacific Islander Women, and Hispanic or Latina women, so I was less confident that differences in the institutional pairs for those proportions could appropriately be attributed to RCM implementation and not pre-existing differences, even if the difference-in-difference estimations resulted in significant differences between RCM and non-RCM groups.

The results of a flexible, conditional difference-in-difference estimation for the individual differences of the gender and race/ethnicity proportions for assistant professors for the period from the start of the treatment (RCM implementation) until two years afterward, for Treated (RCM) institutions and their corresponding Non-Treated (non-RCM) institutions, are presented in Table 4.57. Two proportions had a significant, negative difference: the proportion of Nonresident Alien men (pnonresm) and the proportion of Black or African American women (pblackw) assistant professors. I observed a small, negative change in the mean proportion of Nonresident Alien men (pnonresm) assistant professors at RCM institutions and a positive change at non-RCM institutions from implementation to two years following implementation. This change in means between the two groups was significant at p=0.014. The growth in the mean proportion of Black or African American women (pblackw) assistant professors was smaller at RCM institutions than non-RCM institutions, which was significant at p=0.040.

Table 4.57

Flexible, Conditional Difference-in-Difference for Gender and Race Proportions

	M			t-test	
Outcome	RCM	Non-RCM	Diff	*t*	*p*
pasianm	0.006	-0.005	0.011	-1.058	0.308
pblackm	-0.001	-0.005	0.004	-0.667	0.516
phispm	0.007	0.013	-0.006	0.541	0.597
pnativem	0.000	0.000	0.000	-0.023	0.982
pnonresm	-0.015	0.065	-0.080	2.814	0.014*
ptwom	-0.001	-0.002	0.001	-0.679	0.508
punkm	0.014	0.003	0.011	-0.873	0.398
pwhitem	-0.010	0.074	-0.084	2.122	0.052

pasianw	0.001	-0.008	0.009	-0.975	0.346
pblackw	0.005	0.018	-0.013	2.265	0.040*
phaww	0.001	0.000	0.001	-1.003	0.333
phispw	0.001	-0.003	0.004	-0.842	0.414
pnativew	-0.001	0.003	-0.004	1.759	0.100
pnonresw	-0.009	-0.039	0.030	-1.055	0.309
ptwow	0.001	-0.002	0.003	-1.172	0.261
punkw	0.006	0.001	0.005	-0.391	0.702
pwhitew	-0.005	-0.078	0.073	-1.611	0.129

Note. Significant at the **p*<0.05 level. *n*=16.

The results from a mean fixed effect difference-in-difference estimation for the 2-year period beginning with the year of RCM implementation for proportion of assistant professors by gender and race/ethnicity are displayed in Table 4.58. According to the mean fixed effects DID estimation, RCM implementation had no significant effect on gender and race/ethnicity proportions, except for the proportions of Nonresident Alien men and Nonresident Alien women.

Table 4.58

Mean Fixed Effects Difference-in-Difference for Proportions of Assistant Professors

Variable	β	p	Variable	β	p
pasianm	-0.000	0.965	pasianw	-0.002	0.739
pblackm	0.000	0.990	pblackw	0.012	0.185
phawm	-	-	phaww	0.001	0.144
phispm	-0.002	0.656	phispw	0.004	0.424
pnativem	-0.001	0.496	pnativew	-0.001	0.609
pnonresm	-0.030	0.008*	pnonresw	-0.025	0.010*
ptwom	-0.004	0.182	ptwow	-0.001	0.604
punkm	0.011	0.412	punkw	0.011	0.212
pwhitem	-0.016	0.582	pwhitew	0.038	0.084

Note. Significant at **p*<0.05. Analysis was not conducted for phawm as there were no Native Hawaiian or Other Pacific Islander men at RCM institutions in this sample.

The results from a dynamic fixed effect difference-in-difference estimation for the 2-year period beginning with the year of RCM implementation for proportions of assistant professors by gender and race/ethnicity are displayed in Table 4.59. The coefficient of interest (post x treat) and p-value of the first dummy variable interaction for each race/gender proportion are in the columns for Year 1, and the coefficient and p-value of the second dummy variable interaction are in the columns Year2. According to the dynamic fixed effects DID estimation, RCM implementation had no significant effect on gender and race/ethnicity proportions, except for the proportions of Nonresident Alien men and Nonresident Alien women.

Table 4.59

Dynamic Fixed Effects Difference-in-Difference for Proportions of Assistant Professors

Variable	Year 1		Year 2		Variable	Year 1		Year 2	
	β	*p*	*β*	*p*		*β*	*p*	*β*	*p*
pasianm	-0.003	0.833	0.002	0.858	pasianw	-0.007	0.350	0.003	0.644
pblackm	0.001	0.900	-0.000	0.938	pblackw	0.015	0.099	0.008	0.385
phawm	-	-	-	-	phaww	0.000	0.346	0.001	0.225
phispm	-0.002	0.602	-0.003	0.724	phispw	0.004	0.453	0.005	0.415
pnativem	-0.001	0.391	-0.000	0.652	pnativew	0.000	0.895	-0.001	0.286
pnonresm	-0.026	0.006*	-0.035	0.017*	pnonresw	-0.026	0.033*	-0.025	0.017*
ptwom	-0.003	0.275	-0.004	0.119	ptwow	-0.001	0.530	-0.001	0.712
punkm	0.005	0.780	0.018	0.229	punkw	0.016	0.275	0.006	0.518
pwhitem	-0.009	0.722	-0.024	0.520	pwhitew	0.027	0.191	0.048	

Note. Significant at **p*<0.05. Analysis was not conducted for phawm as there were no Native Hawaiian or Other Pacific Islander men at RCM institutions in this sample.

The results of a fourth difference-in-difference estimation for nsalary are presented in Table 4.60. I added the covariates of fall undergraduate enrollment (ug), fall graduate enrollment (grad), unionization, urbanization, and Carnegie classification to the fixed effects regression model. There was evidence that RCM implementation negatively impacted pnativem, ptwom, pwhitem, and pnonresw and evidence that RCM positively impacted pblackw, phaww, and pwhitew. Carnegie Classification had a significant negative relationship for pnativem and ptwow. Fall graduate enrollment had a positive, significant relationship on pblackm, phispm, and ptwom. Fall undergraduate enrollment had a positive, significant relationship on pblackm, pwhitem, phispw, and pwhitew. Urbanization had a negative, significant relationship to pblackm, pasianw, and pnativew, and a postive, significant relationship to pnonresm.

Table 4.60

Fixed Effects Difference-in-Difference with Covariates for Assistant Professors

	treatxpost	carnegie	grad	ug	urban	_cons
pasianm	-0.002 (0.785)	0.019 (0.106)	0.000 (0.532)	0.000 (0.122)	-0.002 (0.213)	0.130 (0.042)
pblackm	-0.002 (0.647)	0.003 (0.492)	0.000 (0.020)*	0.000 (0.003)*	-0.002 (0.002)*	0.081 (0.009)
phispm	0.002 (0.618)	0.001 (0.801)	0.000 (0.040)*	0.000 (0.358)	0.000 (0.573)	0.017 (0.633)
pnativem	-0.002 (0.036)*	-0.001 (0.001)*	0.000 (0.312)	0.000 (0.259)	0.000 (0.058)	-0.010 (0.166)
pnonresm	-0.023 (0.106)	-0.016 (0.224)	0.000 (0.894)	0.000 (0.747)	0.005 (0.007)*	0.032 (0.769)
ptwom	-0.005 (0.002)*	-0.001 (0.755)	0.000 (0.001)*	0.000 (0.251)	0.000 (0.388)	-0.033 (0.016)
punkm	0.006 (0.471)	-0.020 (0.113)	0.000 (0.411)	0.000 (0.119)	-0.001 (0.606)	0.003 (0.962)
pwhitem	-0.034 (0.048)*	0.021 (0.235)	0.000 (0.993)	0.000 (0.000)*	-0.001 (0.618)	-0.079 (0.449)
pasianw	-0.005 (0.470)	0.004 (0.578)	0.000 (0.237)	0.000 (0.052)	-0.003 (0.018)*	0.038 (0.522)
pblackw	0.011 (0.040)*	0.002 (0.700)	0.000 (0.264)	0.000 (0.080)	-0.002 (0.062)	0.084 (0.058)
phaww	0.001 (0.013)*	0.000 (0.248)	0.000 (0.402)	0.000 (0.838)	0.000 (0.480)	0.001 (0.762)
phispw	0.000 (0.984)	-0.004 (0.535)	0.000 (0.407)	0.000 (0.003)*	0.000 (0.349)	-0.062 (0.060)
pnativew	-0.001 (0.353)	0.001 (0.131)	0.000 (0.657)	0.000 (0.482)	-0.001 (0.001)*	0.007 (0.336)
pnonresw	-0.020 (0.022)*	-0.007 (0.427)	0.000 (0.614)	0.000 (0.587)	0.002 (0.162)	0.064 (0.338)

ptwow	-0.001 (0.490)	-0.003 (0.023)*	0.000 (0.072)	0.000 (0.198)	0.000 (0.764)	-0.010 (0.349)
punkw	0.004 (0.630)	-0.001 (0.300)	0.000 (0.474)	0.000 (0.909)	0.000 (0.975)	0.062 (0.343)
pwhitew	0.057 (0.001)*	0.020 (0.223)	0.000 (0.518)	0.000 (0.000)*	0.003 (0.129)	0.586 (0.000)

Note. Significant at *$p<0.05$. Coefficients are displayed in tables with p-values in parentheses. Analysis was not conducted for phawm as there were no Native Hawaiian or Other Pacific Islander men at RCM institutions in this sample.

Based on the results of four difference-in-difference estimation models that used a nearest neighbor matching process to compare RCM and non-RCM institutions, there was limited evidence that RCM implementation had a significant effect on institutional gender and race/ethnicity proportions of assistant professors on the tenure track equated to 9-month contracts at 4-year degree-granting public doctoral research universities. Three difference-in-difference estimations provided evidence that RCM implementation was negatively associated with the proportion of Nonresident Alien men and Nonresident Alien Women assistant professors. There were no other significant differences consistently found between gender and race/ethnicity proportions for assistant professors by RCM implementation.

In summary, based on several difference-in-difference analyses, I found no evidence of a relationship between RCM implementation and institutional average salary equated to 9-month contracts for assistant professors or institutional average salary of assistant professors by gender at public, 4-year, degree-granting doctoral research universities. I also found no evidence that RCM implementation had a significant effect on proportions of men or women assistant professors at these institutions. I found consistent evidence that RCM implementation had a significant, negative effect on the proportion of Nonresident Alien men assistant professors and the proportion of Nonresident Alien women assistant professors.

Results of ASEE Analyses

The results of a nearest neighbor matching process and difference-in-difference estimation of engineering assistant professor proportions by gender and gender and race/ethnicity by RCM implementation are presented in this section. Prior to matching, the analytic sample for ASEE data was 1,053 and after matching the analytic sample was 144. RQ3 asked, *What is the relationship between RCM implementation and the <u>proportion of assistant professors of engineering</u> at public doctoral universities when considering <u>gender</u>?* The descriptions of variables for RQ3 may be found in Table 3.3. To explore RQ3, I repeated the analysis described for RQ2a, changing the dependent variable to the proportion of men engineering assistant professors (*pengasstm*). I then repeated the analysis changing the dependent variable to the proportion of women engineering assistant professors (*pengasstw*). The results of the nearest neighbor matching process and difference-in-difference estimation for RQ3a are presented in Tables 4.61 – 4.66.

The results of the nearest neighbor matching process for the outcome of proportions of men and women engineering assistant professors are displayed in Table 4.61. The pairing of institutions based on proportion of men engineering assistant professors, the outcome variable pengasstm, one year prior to RCM implementation was the same as the pairing of institutions based on the proportion of women engineering assistant professors, the outcome variable pengasstw. Since the gender proportions for assistant professors are inversely related, the non-RCM institutions in the matched pairs were the same for this set of outcomes.

Table 4.61

Matched Sample for Proportions of Engineering Assistant Professors by Gender

Pair	Year	RCM Institution	Non-RCM Institution	
			Men	Women
1	2012	Texas Tech University	University of Nevada-Las Vegas	University of Nevada-Las Vegas
2	2014	Auburn University	Florida Atlantic University	Florida Atlantic University
3	2014	Ohio University	Oklahoma State University	Oklahoma State University
4	2015	University of Virginia	University of Iowa	University of Iowa
5	2016	University of Arizona	North Carolina State University at Raleigh	North Carolina State University at Raleigh
6	2016	University of California-Davis	University of Colorado Boulder	University of Colorado Boulder
7	2016	University of California-Riverside	University of Nebraska-Lincoln	University of Nebraska-Lincoln
8	2017	George Mason University	University of Maryland-College Park	University of Maryland-College Park

Note. Year equals Fiscal Year of RCM implementation.

To evaluate the similarity of the matched sample, I checked the means and variance ratios for the covariate distributions for each of the RCM and non-RCM pairs for proportion of men engineering assistant professors (pengasstm) and women engineering assistant professors (pengasstw). The results are displayed in Table 4.62. Since the p-values were all above 0.05, I concluded that the means of the matching variables grad_pre1, ug_pre1, carnegie_pre1, urban_pre1, and outcome_dev were balanced for pengasstm and pwomen. The variance ratio indicated balanced samples since no variable's variance ratio fell outside of the 0.20-4.99 range in the F-distribution.

Table 4.62

Evaluation of Engineering Gender Proportions Using Means and Variance Ratios

	pengasstm			pengasstw		
Variable	*t*	*p*	Variance	*t*	*p*	Variance
grad_pre1	-0.190	0.852	1.380	-0.190	0.852	1.380
ug_pre1	-0.090	0.928	3.680	-0.090	0.928	3.680
carnegie_pre1	0.000	1.000	1.000	0.000	1.000	1.000
urban_pre1	0.340	0.743	1.090	0.340	0.743	1.090
outcome_dev	0.460	0.653	0.400	-0.460	0.653	0.400

Note. Significant at *$p<0.05$. Unbalanced samples if variance ratio outside [0.20; 4.99].

The results of Rubin's test provided evidence that the samples were unbalanced for pengasstm and pengasstw. Rubin's B was greater than 25% for both variables, which indicated the samples were not balanced. For pengasstm and pengasstw, B = 69.4%. Rubin's R also indicated the samples were unbalanced, since Rubin's R fell slightly outside of the range of 0.5 to 2, with R=0.49 for both pengasstm and pengasstw.

I conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of men engineering assistant professors (pengasstm) and proportion of women engineering assistant professors (pengasstw), which are displayed in Figure 4.13. The covariate distributions for fall graduate enrollment (grad) were fairly well matched for pengasstm and pengasstw with one outlier pairing. There were two outlier pairings each for fall undergraduate enrollment (ug) for pengasstm and pengasstw. The covariate distributions for Carnegie Basic Classification (carnegie) matched exactly and one pair was not well matched on degree of urbanization (urban) for each proportion. The outcome distributions for pengasstm and pengasstw had significant variation and were not well matched.

Figure 4.13

Plots of Matched Samples for Proportion of Engineering Assistant Professors by Gender

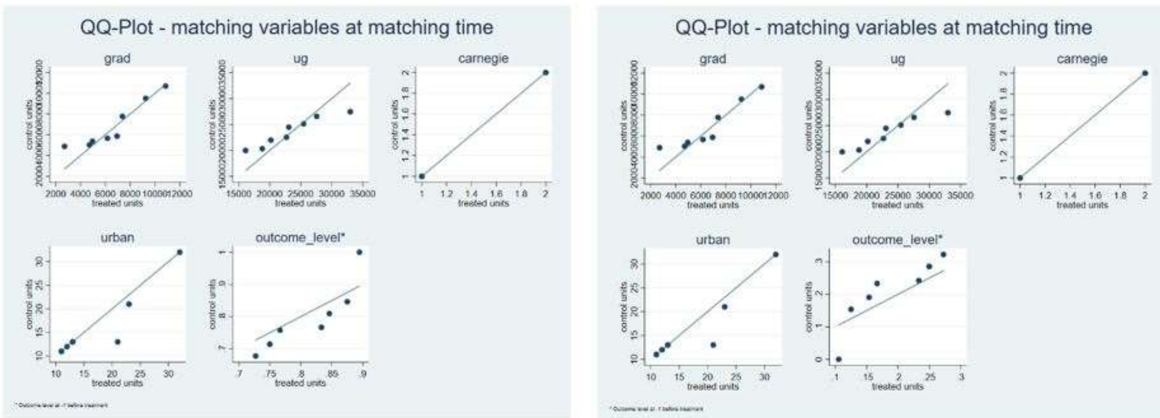

Figure 4.13. Plots for Men (Left) and Women (Right) Engineering Assistant Professors

The Kolmogorov-Smirnov tests for equality of distribution indicated no significant differences in the distributions for the matching continuous variables between the RCM and non-RCM groups. The results are presented in Table 4.63. The corrected p-value was greater than 0.05 for the covariates for pengasstm and pengasstw, so the covariate distributions between RCM and non-RCM groups were not significantly different for either outcome.

Table 4.63

Kolmogorov-Smirnov Evaluation of Matched Samples for Gender Proportions

Variable	*p*	Variable	*p*
pengasstm		pengasstw	
grad_pre1	0.516	grad_pre1	0.516
ug_pre1	0.935	ug_pre1	0.935
outcome_dev	0.935	outcome_dev	0.935
Combined K-S	0.516	Combined K-S	0.516

Note. Corrected p-value = *p*. Significant at **p*<0.05.

The results of the Chi-Square tests for distribution equality of the categorical matching variables for proportion of men assistant professors (pengasstm) and women (pengasstw) are displayed in Table 4.64. The Pearson Chi-Square test statistic for carnegie_pre1 was 0.000 (p=1.000) since institutions matched exactly on Carnegie Basic Classification. The Pearson Chi-Square test statistic for urban_pre1 was 1.200 (p=0.945) for both pengasstm and pengasstw, which indicated balanced samples for both outcomes. Approximately half of the results of the evaluations of matched pairs demonstrated that the covariate distributions used for matching were not significantly different, so I less confident that there were not preexisting differences in the RCM and non-RCM groups for pengasstm and pengasstw based on these covariates.

Table 4.64

Chi-Square Test Evaluation of Matched Samples for Engineering Gender Proportions

Variable	χ^2	p	Variable	χ^2	p
pengasstm			pengasstw		
carnegie_pre1	0.000	1.000	carnegie_pre1	0.000	1.000
urban_pre1	1.200	0.945	urban_pre1	1.200	0.945

Note. Significant at *p<0.05.

The nearest neighbor matching process for RQ3 provided partial evidence for balanced matched samples between the RCM and non-RCM groups for proportions of men (pengasstm) and women (pengasstw) engineering assistant professors. The evaluation of means and variance ratios and chi-square test evaluation indicated balanced samples and the Kolmogorov-Smirnov tests for equality of distribution indicated no significant differences in groups. However, Rubin's test and a visual plot examination did not provide evidence of balanced samples for either gender proportion. Therefore, since four out of six tests indicated no significant differences in groups, I cautiously assumed the samples were well matched.

The results of the conditional, flexible difference-in-difference estimation for RQ3 are presented in Table 4.65. The differences between the RCM and non-RCM groups were not significant for either gender proportion of engineering assistant professors.

Table 4.65

Flexible, Conditional Difference-in-Difference for Engineering Assistant Professors

		M			t-test	
Outcome	*n*	RCM	Non-RCM	Diff	*t*	*p*
pengasstm	16	0.031	0.100	-0.069	1.544	0.145
pengasstw	16	-0.031	-0.100	0.069	-1.544	0.145

Note. Significant at the *p<0.05 level.

The results from three fixed effect difference-in-difference estimation are displayed in Table 4.66. Neither the mean fixed effect difference-in-difference estimation nor the yearly, dynamic treatment effect difference-in-difference estimation for the 2-year period beginning with the year of RCM implementation showed significant effects on the proportion of men (pengasstm) or women (pengasstw) engineering assistant professors. Then, I added the covariates of Carnegie Classification (carnegie), fall undergraduate enrollment (ug), fall graduate enrollment (grad), and degree of urbanization (urban) to the fixed effects model. The differences between the RCM and non-RCM groups were not significant for either gender proportion for any of these fixed effects difference-in-difference estimations.

Table 4.66

Fixed Effects Difference-in-Difference for Assistant Professors Proportions by Gender

Variable	*β*	*p*	Variable	*β*	*p*
Mean Fixed Effects Model					
pengasstm	0.010	0.780	pengasstw	-0.010	0.780
Dynamic Fixed Effects Model					

pengasstm			pengasstw		
Year 1	0.009	0.803	Year 1	-0.009	0.803
Year 2	0.010	0.813	Year 2	-0.010	0.813
Fixed Effects Model with Covariates					
pengasstm			pengasstw		
treatxpost	0.004	0.888	treatxpost	-0.004	0.888
carnegie	0.086	0.074	carnegie	-0.086	0.074
grad	0.000	0.799	grad	0.000	0.799
ug	0.000	0.441	ug	0.000	0.441
urban	-0.001	0.873	urban	0.001	0.873
_cons	0.810	0.009	_cons	0.190	0.535

Note. Significant at **p*<0.05.

Based on the results of four difference-in-difference estimation models that used a nearest neighbor matching process to compare RCM and non-RCM institutions, there was no evidence that RCM implementation between FY2011 – FY2019 had a significant effect on institutional proportions of men or women engineering assistant professors at 4-year degree-granting public doctoral research universities.

The results for RQ3a (*proportion of assistant professors of engineering at public doctoral universities when considering intersection of gender and race/ethnicity*) are presented in Tables 4.67 – 4.76. The results of the nearest neighbor matching process for men assistant professors by race/ethnicity and RCM implementation are presented in Table 4.67 and the results of the nearest neighbor matching process for women assistant professors by race/ethnicity and RCM implementation are presented in Table 4.68. The pairing of institutions based on proportions of men and women assistant professors by race/ethnicity differed based on the inclusion of the proportion outcome variables.

Table 4.67

Matched Samples for Men Engineering Assistant Professors by Race and RCM

	RCM Institutions			
Proportion	Texas Tech University (2012)	Auburn University (2014)	Ohio University (2014)	University of Virginia (2015)
paamm	University of North Texas	Western Michigan University	Oklahoma State University	University of Kansas
pafm	University of Nevada-Las Vegas	Northern Arizona University	Oklahoma State University	University of Kansas
phispm	Old Dominion University	Western Michigan University	Oklahoma State University	University of Kansas
ptwom	University of Nevada-Las Vegas	Western Michigan University	Oklahoma State University	University of Kansas
punkm	University of Nevada-Las Vegas	Florida Atlantic University	Oklahoma State University	University of Iowa
pwm	University of Akron Main Campus	Northern Arizona University	Oklahoma State University	University of Iowa
	RCM Institutions			
Proportion	University of Arizona (2016)	University of California – Davis (2016)	University of California – Riverside (2016)	George Mason University (2017)
paamm	North Carolina State University at Raleigh	University of Nebraska-Lincoln	University of Nebraska-Lincoln	University of Maryland-College Park
pafm	University of Houston	Virginia Commonwealth University	University of Nebraska-Lincoln	University of Maryland-College Park
phispm	North Carolina State University at Raleigh	University of Kentucky	University of Louisville	University of Maryland-College Park
ptwom	University of Houston	University of Missouri-Columbia	University of Nebraska-Lincoln	University at Buffalo
punkm	University of Houston	University of Missouri-Columbia	University of Nebraska-Lincoln	University of Maryland-College Park
pwm	University of Houston	University of Georgia	University of Louisville	University of Maryland-College Park

Note. (Year) = Fiscal Year of RCM implementation.

Table 4.68

Matched Samples for Women Engineering Assistant Professors by Race and RCM

	RCM Implementation			
Proportion	Texas Tech University (2012)	Auburn University (2014)	Ohio University (2014)	University of Virginia (2015)
paamw	Old Dominion University	Western Michigan University	Oklahoma State University	University of Kansas
pafw	University of Nevada-Las Vegas	Western Michigan University	Oklahoma State University	University of Kansas
phispw	Old Dominion University	Northern Arizona University	Oklahoma State University	University of Kansas
ptwow	University of Nevada-Las Vegas	Western Michigan University	Oklahoma State University	University of Kansas
punkw	University of Nevada-Las Vegas	Florida Atlantic University	Oklahoma State University	University of Iowa
pww	University of Nevada-Las Vegas	Western Michigan University	Oklahoma State University	University of Kansas
	RCM Implementation			
Proportion	University of Arizona (2016)	University of California – Davis (2016)	University of California – Riverside (2016)	George Mason University (2017)
paamw	University of Houston	Virginia Commonwealth University	University of Louisville	University of Maryland-College Park
pafw	University of Houston	University of Missouri-Columbia	University of Nebraska-Lincoln	University at Buffalo
phispw	University of South Florida	University of Iowa	University of Nebraska-Lincoln	University at Buffalo
ptwow	University of Houston	University of Missouri-Columbia	University of Nebraska-Lincoln	University of Maryland-College Park
punkw	University of Houston	University of Missouri-Columbia	University of Nebraska-Lincoln	University of Maryland-College Park
pww	University of Houston	Virginia Commonwealth University	University of Louisville	University of Maryland-College Park

Note. (Year) = Fiscal Year of RCM implementation.

To evaluate the similarity of the matched groups for proportions of Asian, Black or African American, Hispanic or Latino, Two or More Races, Race/Ethnicity Unknown, and White men and women engineering assistant professors, I checked the means and variances for the covariate distributions for each of the RCM and non-RCM groups. All universities matched exactly by Basic Carnegie Classification (carnegie_pre1), so the p-values for the means were all

1.000 and the variance ratio was all 1.000, so they are not included in Table 4.69. All other covariate results are displayed in Table 4.69.

Outcome variance ratios were missing for pafw, phaww, and ptwom because there were not enough observations prior to RCM implementation for computation. There were no comparisons for pafm and ptwow because there were no readable proportions in the control group prior to RCM implementation at the corresponding university. The p-values for the other covariate means were all above 0.05. Therefore, I concluded that the means of the matching variables were balanced for all other proportions. I removed the _pre1 suffix from the matching variables in Table 4.69 for readability. Since no variable's variance ratio falls outside of the 0.20-4.99 range in the F-distribution, the matched samples for all other gender and race/ethnicity proportions were balanced.

Table 4.69

Evaluation of Matching for Engineering Gender Proportions by Means and Variance

	Men			Women		
Variable	*t*	*p*	Variance	*t*	*p*	Variance
Asian (paamm and paamw)						
Grad	-0.660	0.518	1.540	-0.230	0.819	1.880
Ug	0.000	0.998	1.750	0.400	0.695	0.920
Urban	0.370	0.719	1.070	0.370	0.719	1.070
Outcome	0.250	0.809	0.640	-0.010	0.989	0.980
African American or Black (pafm and pafw)						
Grad	-0.090	0.932	1.560	-0.160	0.871	2.200
Ug	-0.060	0.955	1.320	0.230	0.825	1.140
Urban	0.370	0.719	1.070	0.370	0.719	1.070
Outcome	.	.	.	1.000	0.334	.
Hispanic or Latino (phisp)						
Grad	-0.380	0.712	1.540	-0.320	0.752	1.170
Ug	1.030	0.321	2.200	0.700	0.494	1.820
Urban	0.400	0.696	1.050	0.340	0.743	1.090

	Men			Women		
Variable	*t*	*p*	Variance	*t*	*p*	Variance
Outcome	0.240	0.812	1.390	0.000	0.999	0.930
Two or More Races (ptwom and ptwow)						
Grad	-0.160	0.871	2.200	-0.250	0.806	1.740
Ug	0.230	0.825	1.140	-0.140	0.894	1.100
Urban	0.370	0.719	1.070	0.370	0.719	1.070
Outcome	1.000	0.334	.	.	.	.
Race/Ethnicity Unknown (punkm and punkw)						
Grad	-0.230	0.824	1.680	-0.230	0.824	1.680
Ug	-0.570	0.577	1.430	-0.570	0.577	1.430
Urban	0.370	0.719	1.070	0.370	0.719	1.070
Outcome	0.370	0.716	2.690	-0.450	0.661	1.090
White (pwm and pww)						
Grad	-0.160	0.877	1.380	-0.250	0.804	1.910
Ug	-0.140	0.889	1.040	0.240	0.813	0.980
Urban	0.370	0.719	1.070	0.370	0.719	1.070
Outcome	-0.180	0.857	2.010	0.370	0.720	0.620

Note. Significant at **p*<0.05. Unbalanced samples if variance ratio outside [0.20; 4.99].

The results of Rubin’s test are provided in Table 4.70. Rubin’s B was greater than 25% for all gender and race/ethnicity proportions for engineering assistant professors, except proportions of African American or Black men and women, which indicated the samples were not balanced. Rubin’s R also indicated the samples were unbalanced, for Asian American men, Hispanic or Latino men, Hispanic or Latina women, and White women.

Table 4.70

Rubin's Test Evaluation of Matched Samples for Engineering Proportions

Variable	B	R	Variable	B	R
paamm	54.6%*	2.18*	paamw	49.0%*	1.01
pafm	21.9%	1.82	pafw	53.3%*	0.89
phispm	93.1%*	4.12*	phispw	62.2%*	3.31*
ptwom	59.7%*	1.02	ptwow	27.3%*	2.20*
punkm	58.6%*	1.86	punkw	50.5%*	1.16
pwm	35.3%*	2.00	pww	39.4%*	2.39*

Note. If Rubin's B>25%*, samples are unbalanced. If Rubin's R outside [0.5; 2]*, samples are unbalanced.

I then conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of Asian men (paamm) and proportion of Asian women (paamw), which are displayed in Figure 4.14. For fall graduate enrollment (grad) and fall undergraduate enrollment (ug), the distributions were somewhat well matched with two outliers for each proportion. Both proportions matched exactly on Carnegie Basic Classification (carnegie) and each proportion had one pair that did not match well based on degree of urbanization (urban). The outcome variable distribution was well matched with only one outlier for each proportion.

Figure 4.14

Plots of Matched Samples for Proportion of Engineering Asian Men and Women

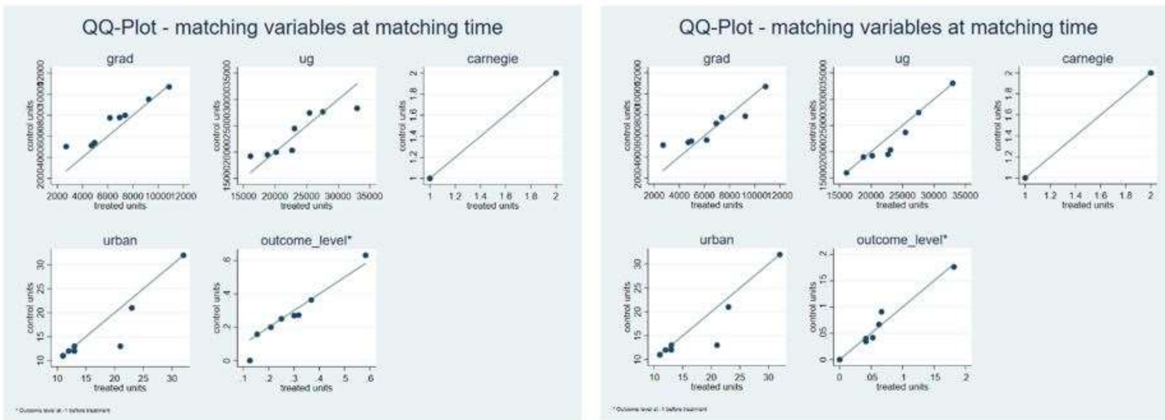

Figure 4.14. Plots of Matched Samples for Proportion of Asian Men (Left) and Women (Right)

I conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of African American or Black men (pafm) and proportion of African American or Black women (pafw) engineering assistant professors, which are displayed in Figure 4.15. The fall graduate enrollment (grad) distributions for each proportion were closely matched with one outlier. For fall undergraduate enrollment (ug), pafm was more closely matched than pafw. The covariate distributions for Carnegie Basic Classification (carnegie) matched exactly and only one pair did not match on degree of urbanization (urban) for each proportion. The outcome variable distribution for pafm was unattainable and the outcome distribution for pafw was a poor match.

Figure 4.15

Matched Samples for Proportion of Engineering African American Men and Women

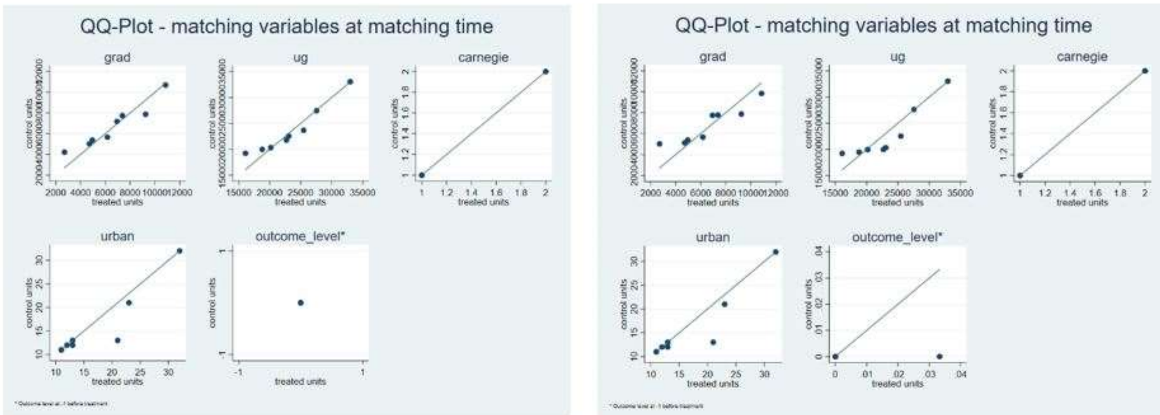

Figure 4.15. Plots of Matched Samples for African American Men (Left) and Women (Right)

I conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of Hispanic or Latino men (phispm) and proportion of Hispanic or Latina women (phispw), which are displayed in Figure 4.16. The covariate distributions for phispm and phispw were well matched for fall graduate enrollment (grad) with one outlier. Fall undergraduate enrollment (ug) was not well matched for either proportion. The covariate distributions for Carnegie Basic Classification (carnegie) matched exactly and only one pair was not well matched on degree of urbanization (urban) for each proportion. The outcome distributions for phispm and phispw were not well matched.

Figure 4.16

Plots of Matched Samples for Proportion of Engineering Hispanic or Latino Men and Women

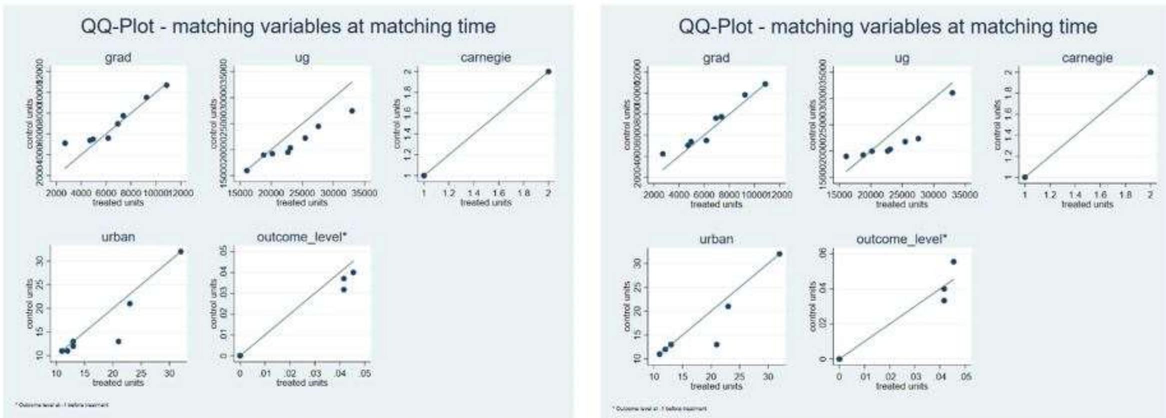

Figure 4.16. Plots of Matched Samples for Hispanic Men (Left) and Women (Right)

I conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of Two or More Races men (ptwom) and proportion of Two or More Races women (ptwow), which are displayed in Figure 4.17. The covariate distribution for fall graduate enrollment (grad) were well matched for ptwom and ptwow with one outlying pair. There was slightly more variation in the distribution for fall undergraduate enrollment (ug) for ptwom than ptwow. The covariate distributions for Carnegie Basic Classification (carnegie) matched exactly and one pair was not well matched on degree of urbanization (urban) for each proportion. The outcome distributions for ptwom and ptwow were not well matched for most institutional pairs one year prior to RCM implementation.

Figure 4.17

Plots of Matched Samples for Proportion of Engineering Two or More Races Men and Women

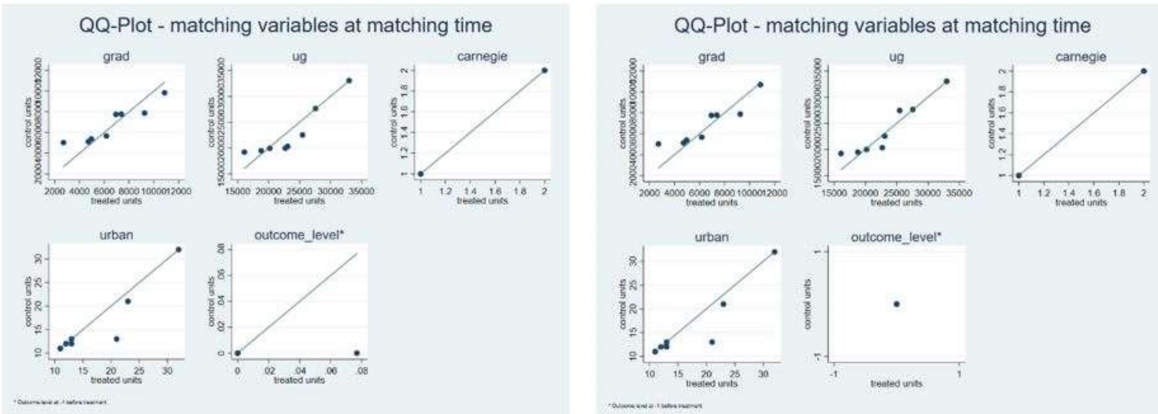

Figure 4.17. Plots of Matched Samples for Two or More Races Men (Left) and Women (Right)

I conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of Race/Ethnicity Unknown men (punkm) and proportion of Race/Ethnicity Unknown women (punkw), which are displayed in Figure 4.18. The covariate distributions for fall graduate enrollment (grad) and fall undergraduate enrollment (ug) appeared to be the same and fairly good matches for punkm and punkw. The covariate distributions for Carnegie Basic Classification (carnegie) matched exactly and one pair was not well matched on degree of urbanization (urban) for each proportion. There was large variation in the outcome distributions for punkm and punkw.

Figure 4.18

Matched Samples for Proportion of Engineering Race/Ethnicity Unknown Men and Women

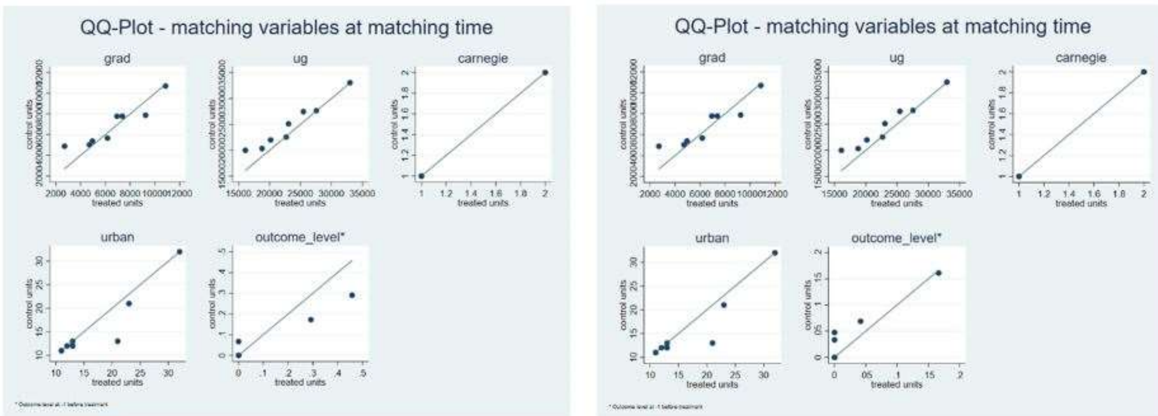

Figure 4.18. Plots for Race/Ethnicity Unknown Men (Left) and Women (Right)

I conducted a visual examination of the Quantile-Quantile Plots for Matched Samples of the proportion of White men (pwm) and proportion of White women (pww) engineering assistant professors, which are displayed in Figure 4.19. The covariate distributions for fall graduate enrollment (grad) were fairly well matched for pwm and pww with one outlier and had more variation than the covariate distributions for fall undergraduate enrollment (ug). The covariate distributions for Carnegie Basic Classification (carnegie) matched exactly and one pair was not well matched on degree of urbanization (urban) for each proportion. The outcome distributions for pwm and pww were fairly well matched with one outlier.

Figure 4.19

Plots of Matched Samples for Proportion of Engineering White Men and Women

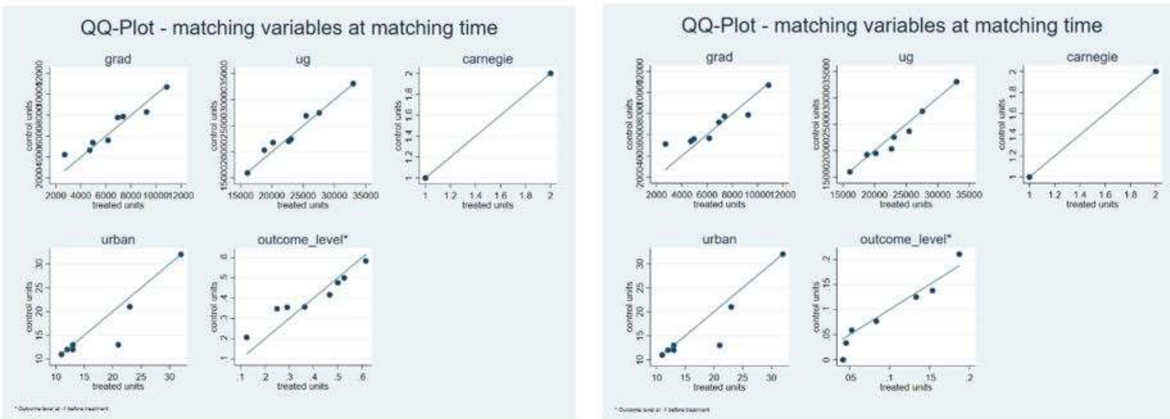

Figure 4.19. Plots of Matched Samples for Proportion of White Men (Left) and Women (Right)

The results of the Kolmogorov-Smirnov tests for equality of distribution are presented in Table 4.71. The Kolmogorov-Smirnov tests indicated no significant differences in the covariate distributions for the matched sample continuous variables between the RCM and non-RCM groups since all corrected p-values were above 0.05.

Table 4.71

Kolmogorov-Smirnov Evaluation of Matching for Engineering Proportions

Variable	grad_pre1	ug_pre1	outcome_dev	Combined K-S
paamm	0.935	0.516	0.935	0.935
pafm	1.000	0.935	0.935	1.000
phispm	0.516	0.516	0.516	0.516
ptwom	1.000	0.516	0.516	1.000
punkm	0.935	0.935	0.935	0.935
pwm	0.935	0.935	0.935	0.935
paamw	0.935	0.516	0.935	0.935
pafw	1.000	0.516	0.516	1.000
phispw	0.935	0.935	0.185	0.935

Variable	grad_pre1	ug_pre1	outcome_dev	Combined K-S
ptwow	1.000	0.516	0.935	1.000
punkw	0.935	0.935	0.935	0.935
pww	0.516	0.516	0.935	0.516

Note. Numbers displayed are corrected p-values. Significant at **p*< 0.05.

Table 4.72 displays the results of the Chi-Square tests for distribution equality of the categorical matching variables for proportion of men and women assistant professors by race/ethnicity for the categorical matching variables, Carnegie Basic Classification (carnegie_pre1) and Degree of Urbanization (urban_pre1). The _pre1 suffix has been removed from the table for readability. A significant p-value (less than 0.05) indicates the samples are not balanced. The Pearson Chi-Square test statistics for carnegie_pre1 and urban_pre1 were not significant, which indicated balanced matched samples for all engineering assistant professor proportions. In summary, the results of the majority of evaluations of matched pairs demonstrated that the covariate distributions used for matching were not significantly different, so I was reasonably confident that there were not preexisting differences in the RCM and non-RCM groups for engineering assistant professor gender and race/ethnicity proportions based on these covariates.

Table 4.72

Chi-Square Evaluation of Matched Samples for Engineering Proportions

	carnegie		urban			carnegie		urban	
Variable	χ^2	*p*	χ^2	*p*	Variable	χ^2	*p*	χ^2	*p*
paamm	0.000	1.000	1.333	0.931	paamw	0.000	1.000	1.333	0.931
pafm	0.000	1.000	1.333	0.931	pafw	0.000	1.000	1.333	0.931
phispm	0.000	1.000	1.200	0.945	phispw	0.000	1.000	1.200	0.945
ptwom	0.000	1.000	1.333	0.931	ptwow	0.000	1.000	1.333	0.931

punkm	0.000	1.000	1.333	0.931	punkw	0.000	1.000	1.333	0.931
pwm	0.000	1.000	1.333	0.931	pww	0.000	1.000	1.333	0.931

Note. Significant at *p<0.05. Analysis was not conducted for phawm as there were no Native Hawaiian or Other Pacific Islander men at RCM institutions in this sample.

The results of a flexible conditional difference-in-difference estimation for the individual differences of the gender and race/ethnicity proportions for assistant professors from RCM implementation until two years afterward, for RCM institutions and their corresponding Non-RCM institutions are presented in Table 4.73. There were no significant differences in gender and race/ethnicity proportions of engineering professors by RCM implementation.

Table 4.73

Flexible, Conditional Difference-in-Difference for Engineering Proportions

	M			t-test	
Outcome	RCM	Non-RCM	Diff	*t*	*p*
paamm	-0.023	0.115	-0.138	1.744	0.103
pafm	0.002	0.005	-0.003	0.240	0.814
phispm	0.005	0.075	-0.070	1.915	0.076
ptwom	0.063	-0.022	0.085	-1.126	0.279
punkm	0.092	-0.019	0.111	-2.001	0.065
pwm	-0.108	-0.059	-0.049	0.646	0.529
paamw	-0.016	0.003	-0.019	0.819	0.426
pafw	0.000	0.001	-0.001	0.194	0.849
phispw	-0.005	-0.007	0.002	-0.212	0.835
ptwow	0.010	-0.019	0.030	-1.721	0.107
punkw	0.012	-0.019	0.031	-0.871	0.398
pww	-0.032	-0.007	-0.025	0.648	0.528

Note. Significant at the *p<0.05 level. n=16.

The results from a mean fixed effect difference-in-difference estimation for the 2-year period beginning with the year of RCM implementation for proportion of assistant professors by race/ethnicity and gender are displayed in Table 4.74. According to the mean fixed effects DID estimation, RCM implementation had a significant negative effect on pwm. There were no other significant differences for any other groups.

Table 4.74

Mean Fixed Effects Difference-in-Difference for Engineering Proportions

Variable	*β*	*p*	Variable	*β*	*p*
paamm	0.054	0.441	paamw	-0.030	0.281
pafm	-0.006	0.517	pafw	-0.009	0.302
phispm	-0.012	0.410	phispw	-0.011	0.248
ptwom	0.031	0.324	ptwow	0.006	0.235
punkm	0.088	0.149	punkw	0.016	0.078
pwm	-0.097	0.025*	pww	-0.039	0.356

Note. Significant at *p<0.05.

The results from a dynamic fixed effect difference-in-difference estimation and a yearly, dynamic treatment effect difference-in-difference estimation for the 2-year period beginning with the year of RCM implementation for proportions of engineering assistant professors by gender and race/ethnicity are displayed in Table 4.75. The coefficient and p-value of the first dummy variable interaction (year one to year two) for each race/gender proportion are in the Year 1 column and the coefficient and p-value of the second dummy variable interaction (year one to year two) are in the Year 2 column. According to the dynamic fixed effects difference-in-difference estimation, RCM implementation had no significant effect on the race/ethnicity and gender proportion of any groups of engineering assistant professors.

Table 4.75

Dynamic Fixed Effects Difference-in-Difference for Engineering Proportions

Variable	Year 1		Year 2		Variable	Year 1		Year 2	
	β	*p*	*β*	*p*		*β*	*p*	*β*	*p*
paamm	-0.026	0.670	0.000	0.996	paamw	-0.008	0.710	-0.006	0.793
pafm	0.001	0.910	-0.013	0.236	pafw	-0.010	0.195	-0.008	0.427
phispm	-0.012	0.376	-0.011	0.477	phispw	-0.011	0.329	-0.011	0.210
ptwom	0.001	0.964	0.061	0.324	ptwow	-0.001	0.797	0.014	0.194
punkm	0.071	0.333	0.106	0.071	punkw	0.019	0.288	0.013	0.443
pwm	-0.058	0.247	-0.136	0.050	pww	-0.025	0.561	-0.053	0.243

Note. Significant at **p*<0.05.

I added the covariates of Carnegie Classification (carnegie), fall graduate enrollment (grad), fall undergraduate enrollment (ug), and urbanization (urban) to a fixed effects difference-in-difference model. The results are displayed in Table 4.76. There was no significant difference between RCM and non-RCM groups in gender and race/ethnicity proportions of engineering assistant professors.

Table 4.76

Fixed Effects Difference-in-Difference with Covariates for Engineering Proportions

	treatxpost	carnegie	grad	ug	urban	_cons
paamm	-0.004 (0.888)	-0.086 (0.074)	0.000 (0.799)	0.000 (0.441)	0.001 (0.873)	0.190 (0.535)
paafmm	-0.019 (0.142)	0.054 (0.005)*	0.000 (0.006)*	0.000 (0.552)	0.002 (0.422)	-0.309 (0.004)
phispm	-0.008 (0.312)	-0.018 (0.144)	0.000 (0.911)	0.000 (0.151)	0.002 (0.113)	-0.067 (0.329)
ptwom	0.026 (0.263)	0.014 (0.682)	0.000 (0716)	0.000 (0.416)	-0.002 (0.469)	0.160 (0.348)
punkm	0.057 (0.119)	0.228 (0.000)*	0.000 (0.593)	0.000 (0.987)	-0.001 (0.829)	-0.374 (0.207)
pwm	-0.056 (0.113)	-0.138 (0.010)*	0.000 (0.280)	0.000 (0.113)	0.001 (0.828)	0.497 (0.049)
paamw	0.023 (0.621)	-0.229 (0.000)*	0.000 (0.306)	0.000 (0.730)	-0.001 (0.870)	0.815 (0.027)

paafmw	-0.007 (0.149)	0.005 (0.506)	0.000 (0.553)	0.000 (0.813)	0.000 (0.907)	-0.026 (-0.100)
phispw	-0.003 (0.581)	0.000 (0.992)	0.000 (0.226)	0.000 (0.585)	0.000 (0.685)	0.015 (0.789)
ptwow	0.007 (0.197)	0.003 (0.657)	0.000 (0.910)	0.000 (0.654)	0.000 (0.841)	0.008 (0.840)
punkw	0.007 (0.197)	0.003 (0.657)	0.000 (0.910)	0.000 (0.654)	0.000 (0.841)	0.000 (0.841)
pww	-0.045 (0.061)	-0.044 (0.212)	0.000 (0.392)	0.000 (0.606)	-0.003 (0.517)	0.063 (0.740)

Note. Significant at *p<0.05. Coefficients are displayed in tables with p-values in parentheses.

Based on the results of four difference-in-difference estimation models that used a nearest neighbor matching process to compare RCM and non-RCM institutions, there was little evidence that RCM implementation had a significant effect on institutional race/ethnicity and gender proportions of engineering assistant professors at 4-year degree-granting public doctoral research universities. The mean fixed effects DID estimation did show a negative relationship between RCM implementation and the proportion of White men engineering assistant professors, however, there were no other significant differences for any other groups or for the flexible, conditional difference-in-difference estimation, the dynamic fixed effects difference-in-difference estimation, or a fixed effects difference-in-difference estimation with covariates.

In summary, when focusing on assistant professors of engineering, I found little evidence that RCM implementation had a significant effect on institutional race/ethnicity and gender proportions of engineering assistant professors at 4-year degree-granting public doctoral research universities. One difference-in-difference estimation did show a negative relationship between RCM implementation and the proportion of White men engineering assistant professors. There were no other significant differences for any other groups.

Results of Ohio Engineering Analysis

Finally, the results of a nearest neighbor matching process and difference-in-difference estimation of annual salaries of assistant professors of engineering for two public research universities within the state of Ohio, one of which implemented RCM, are presented in the fourth section. RQ4 asked, *What is the relationship between RCM implementation and the annual salaries of assistant professors of engineering at public doctoral universities in Ohio?* Following the matching process used for the prior three research questions, I evaluated the similarity of the RCM (Ohio University) and non-RCM (University of Toledo) matched pair. I was unable to examine the means and variances, Rubin's test, chi-square test, and conduct a visual comparison because of insufficient number of observations. For the categorical matching variables for this procedure, Ohio University and the University of Toledo shared the same Carnegie 2010 Basic Classification of Doctoral University: High Research Activity. However, they differed on urbanization: University of Toledo (City: Large) and Ohio University (Town: Distant).

The results of the two-sample Kolmogorov-Smirnov test for equality of distribution functions for each matched sample for nsalary are displayed in Table 4.77. The two-sample Kolmogorov-Smirnov tests for equality of distribution is used to verify the matching procedure for nsalary based on statistical distance for the continuous matching variables, fall graduate student enrollment and fall undergraduate student enrollment. The Kolmogorov-Smirnov tests indicated no significant differences in the distributions for these variables with a combined, corrected p-value of 0.959. In summary, the evaluation of matched distributions provided evidence that pre-existing differences between Ohio University and the University of Toledo were not significantly different for Carnegie Classification, fall graduate enrollment, and fall undergraduate enrollment.

Table 4.77

Kolmogorov-Smirnov Evaluation of Matched Pair for Ohio University

K-smirnov	Corrected *p*
grad_pre1	0.959
ug_pre1	0.959
outcome_dev	0.959
combined	0.959
Note. Significant at p<0.05.	

I was not overly concerned with the categorical differences in the two institutions because difference-in-difference allowed to compare the *trends* in annual salary of engineering assistant professors at each institution before and after RCM implementation at Ohio University in FY 2014.

To determine the magnitude of the policy impact (RCM implementation), I measured the salary means for the treatment and comparison groups before and after treatment and compared the differences in growth, which is displayed in Table 4.78. Prior to RCM implementation at Ohio University, there appeared to be an inverse relationship of salary between Ohio University and the University of Toledo. Prior to FY 2014, mean salaries at the University of Toledo rose and then declined, while mean salaries at Ohio University declined and then rose. After RCM implementation in FY 2014, the relationship appeared to change. Mean salaries of assistant professors of engineering at Ohio University increased by $14,510 following RCM implementation. Over the same time period, mean salaries of engineering for assistant professors at the University of Toledo decreased by $260. Mean engineering salaries at Ohio University were $15,646 less than at University of Toledo prior to RCM implementation, but that gap decreased to $875 after RCM implementation. I calculated the difference in the group differences to obtain $14,771.

Table 4.78

Comparison of Group Means of Assistant Professor of Engineering Salary by RCM

Institution	Pre	Post	Difference
University of Toledo (Non RCM)	95913	95653	-260
Ohio University (RCM)	80267	94777	14510
			14771
Note. Numbers are rounded to nearest whole number.			

I then ran a panel regression on this data interacting the treat (RCM) variable with the post (before and after RCM implementation) variable to obtain the difference-in-difference estimate. This resulted in an average treatment effect of β=12793.700, meaning that there was a $12,793.70 additional positive change in average salary of assistant professors of engineering at the University of Ohio after RCM implementation, after controlling for preexisting difference tween the University of Ohio and the University of Toledo and the differences in the before and after RCM implementation period for both universities. However, the result was not significant at $p<0.05$.

Table 4.79

Difference-in-Difference of Assistant Professor of Engineering Salary by RCM

Outcome	β	*SE*	*z*	*p*	95% Conf. Interval	
treat x post	12793.700	7412.712	1.730	0.084	-1734.952	27322.340
Note. Significant at the **p*<0.05 level.						

I then ran a second regression and added the covariates of fall undergraduate enrollment (ug), fall graduate enrollment (grad), unionization, urbanization, and Carnegie classification to the regression model. The time invariant variables (unionization, urbanization, and Carnegie classification) were omitted from the model because of collinearity. Neither fall undergraduate enrollment nor fall graduate enrollment had a significant effect. In summary, when focusing on assistant professors of engineering at two Ohio universities, I did not find evidence that RCM implementation had a significant effect on annual salary.

Chapter Five

Discussion and Conclusion

This study examined the relationship between RCM implementation, faculty composition, and faculty compensation through proportions and salaries of assistant professors on the tenure track at public, 4-year, degree-granting doctoral universities. The overarching research question that guided this study was, "*What is the relationship between RCM implementation and faculty composition and faculty compensation at public doctoral universities?*" My study was grounded in the distributive justice and procedural justice tenets of organizational justice theory. Because RCM implementation is associated with increased decision-making power and budgetary responsibility of deans, and thus the potential for varied individual biases to influence decisions, I aimed to identify potential inequities in outcomes (faculty composition and faculty compensation) and inequities by gender and race/ethnicity within these outcomes associated with RCM implementation.

To examine faculty composition, my research focused on proportions of assistant professors, proportions of by gender, and proportions by gender and race/ethnicity at public, doctoral universities that implemented RCM between FY2012 – FY2017 compared to those that did not. I then examined proportions of assistant professors of engineering by gender and proportions of assistant professors of engineering by gender and race/ethnicity at those institutions. To examine faculty compensation, my research focused on institutional average salary of assistant professors, institutional average salary of assistant professors by gender and the intersection of gender and race/ethnicity at public, doctoral universities that implemented RCM between FY2012 – FY 2017 compared to those that did not. I then examined annual salaries of assistant professors of engineering at two public, research doctoral universities in

Ohio, one of which implemented RCM in FY2014, and one that did not. I included covariates of Carnegie Basic Classification, fall undergraduate student enrollment, fall graduate student enrollment, region, urbanization, and unionization in this study. Included in this chapter is a summary of my findings, contributions to the literature, implications for policy and practice, considerations for future research, and the conclusion.

Summary of the Findings

Increasingly, public universities have implemented RCM as one way to increase revenue and transparency, track revenue and expenses, and decentralize responsibility for cost savings and entrepreneurship to the college level, as well as steer strategic planning efforts. Limited prior research has examined the relationship between RCM and outcomes, such as Jaquette et al. (2018)'s study of the effects of RCM on tuition revenue. Prior research on RCM has mainly focused on faculty and administrator perceptions of RCM (Allison, 2009), decision-making in the RCM environment (Cekic, 2008; Veldkamp, 2018), case studies of implementation experiences (Bouillon et al., 2016; Hearn et al., 2006), or single-institution outcomes (Pappone, 2016; Willett, 2013). Empirical evidence of the impact of RCM on faculty composition and faculty compensation was lacking. Absent evidence of the outcomes of RCM, university administrators have implemented a policy for which the impact and consequences are largely unknown.

Focusing solely on individual level predictors of faculty salary has failed to account for critical perspectives on how departmental administrators and expectations influence faculty behavior (Santos, 2007). Organizational justice theory grounded this study by connecting the implementation of RCM model to the diffusion of decision-making throughout the organization and potential association with faculty composition and faculty compensation. Similar to Gehl

(2016)'s finding that increased department head discretion influenced pay inequities for foreign-born STEM faculty, if RCM implementation significantly impacted the decision-making processes or criteria (i.e., procedural justice) as they related to faculty composition, I would have expected to see a change in faculty proportions or salaries (i.e., distributive justice) by gender and/or race/ethnicity. As RCM did not appear to be associated with any changes in faculty composition or compensation practices, one might conclude that RCM implementation as procedural justice (decentralized decision-making of deans or department heads) has not impacted faculty composition or faculty compensation through distributive justice (salary amounts or proportions of who was hired by gender and race/ethnicity) at public, doctoral universities.

Institution-wide analyses. To examine the effect of RCM implementation on faculty compensation, I examined assistant professors on the tenure track using IPEDS data for institutional average salary and institutional average salary for men and women. I then examined the proportions of assistant men and women assistant professors, as well as men and women by race/ethnicity in IPEDS.

Institutional average salary. Four difference-in-difference estimations did not produce any statistically significant evidence that there was a relationship between RCM implementation and institutional average salary of assistant professors or institutional proportions of men or women assistant professors at public doctoral research universities between FY2012 – FY 2017.

As outlined in the literature, there are many determinants of faculty salaries. Institutional and regional predictors include departmental expectations for faculty behavior (Santos, 2007), institutional type (Fairweather, 1995; Luna, 2007; Renzulli et al., 2013), unionization (Clery, 2015; Ogun, 2016), measures of institutional wealth and prestige (Rippner & Toutkoushian, 2015), geographical location (American Association of University Professors, 2018; Ogun, 2016), and political representation (American Association of University Professors, 2018). Individual predictors include research productivity (Grofman, 2009; Hensley, 2014; Hilmer et al., 2015; Stack, 2014), teaching experience (Meyers, 2011; Stack, 2014), full-time employment status (Hensley, 2014), rank (Hensley, 2014; Luna, 2007), academic discipline (Luna, 2007; Stack, 2014), gender (American Association of University Professors, 2018; Meyers, 2011), and race/ethnicity (Carson, 2013; Turner et al., 2008). Absent a population data collection effort that contains institutional and individual predictors of faculty salaries, I was unable to include all the known predictors in my difference-in-difference estimation models. For example, I was unable to gather information for faculty members by discipline at the institutional level, individual level information such as salaries or measures of research productivity, or a time variant measure of unionization from IPEDS. Significant variation in faculty salaries and faculty number by gender and race/ethnicity within institutions may disguise effects of RCM implementation.

Gender and race/ethnicity proportions. Based on the results of four difference-in-difference estimations, there was little evidence that RCM implementation had a significant effect on institutional gender and race/ethnicity proportions of assistant professors at public doctoral research universities, with the exception of proportions of Nonresident Alien men and Nonresident Alien women assistant professors. As defined in IPEDS, a Nonresident Alien is, "A person who is not a citizen or national of the United States and who is in this country on a visa or temporary basis and does not have the right to remain indefinitely." I consistently (three out of four difference-in-difference estimations) found statistically significant evidence that RCM implementation was negatively associated with the proportions of Nonresident Alien men and

Nonresident Alien women assistant professors, but no other consistent differences among gender and racial/ethnic groups emerged.

I likened RCM implementation to policy implementation, and in higher education literature a one to two-year lag has been used to study the effects of policies using the difference-in-difference method (Hu, 2019; Li, 2016). However, the hiring and promotion of tenure track faculty are not quick processes, and two years may not have been a sufficient time period within which to capture effects on faculty composition and faculty salaries by RCM implementation. Further research might examine longer time periods following RCM implementation to determine the optimum window with which to see effects.

Assistant professors of engineering. Engineering is a good choice of field for which to focus in on the outcomes of RCM implementation because Curry et al. (2013) posited schools like engineering fare well in an RCM environment. To examine the effect of RCM implementation on engineering faculty composition, I leveraged the ASEE database. Four difference-in-difference estimation models found relatively no evidence that RCM implementation had a significant effect on institutional gender and gender and race/ethnicity proportions of engineering assistant professors at 4-year degree-granting public doctoral research universities. Only one estimate, the mean fixed effects difference-in-difference estimation, showed a statistically significant negative relationship between RCM implementation and the proportion of White men engineering assistant professors.

The decreasing proportion of White men engineering assistant professors was not a consistent finding, and it may have other explanations, such as changing demographics in the population or the disproportionate promotion of White men engineering assistant professors to the associate and full professor ranks as compared to assistant professors of other genders and races/ethnicities. For example, Gumpertz, Durodoye, Griffith, and Wilson (2017) found that women assistant professors of engineering were more likely to leave an institution without tenure than men, and (McGee et al., 2015) demonstrated that growth among racially marginalized tenured and tenure track engineering faculty has been slow (Asian American, Latino, American Indian, and Hawaiian/Pacific Islander) or has decreased (African American). Thus, because the finding did not consistently appear across estimation models, I urge caution in linking this result to RCM implementation.

To ascertain the effect of RCM implementation on engineering faculty salaries, I conducted an exploratory analysis to compare two public, doctoral universities in Ohio, one of which implemented RCM in FY2014—there was no available inter-state data set containing faculty salary information that could be pared down to the individual faculty level within a College. I examined annual individual salaries of assistant professors of engineering by name and department through the Ohio Higher Ed Salary database from the Buckeye Institute and compared the information against the universities' online course catalogs to establish faculty rosters by rank and discipline.

A standard difference-in-difference estimation with and without covariates did not find evidence that RCM implementation had a significant effect at the $p<0.05$ level (but it was significant at $p<0.1$ level) on annual salaries of assistant professors of engineering at two public 4-year degree-granting public doctoral research universities in Ohio. These findings should be interpreted with caution because of low numbers in the analytic sample size (n=135), and a key assumption of difference-in-difference estimation method was not met (assumption of parallel trends) due to the inverse salary relationship between Ohio University and the University of Toledo prior to RCM implementation at Ohio University. However, because of the differences in average salaries for the RCM institution pre- and post-implementation, these findings point to needed additional research focused at the college and departmental level by discipline to explore the impact of RCM implementation on faculty salaries.

Additional methodological contributions. To mitigate the concerns expressed by Jaquette et al. (2018), I used a nearest neighbor matching process outlined by Dettman et al. (2019) so the difference-in-difference estimations would compare RCM implementation within the matched samples rather than comparing the average treatment effect across all universities adopting RCM, recognizing that RCM models do vary by institution. Dettman et al. (2019) offered detailed examples of a methodological process that used a nearest neighbor matching process with tests to examine the comparability of the matched pairs and three difference-in-difference estimation models (flexible conditional, mean fixed effects, and dynamic fixed effects). My study extends their contribution by replicating the process with real data and interpretations. Additionally, although the authors offered a note that additional covariates might be added to the difference-in-difference model, they did not outline the process and provide an example, which I did in this analysis. My analysis provides an example for other researchers to conduct similar difference-in-difference estimations including known and suspected covariates that also may have relationships with the policy or outcome to better sparse policy effects from other confounding variables. Additionally, for researchers studying faculty composition and compensation, I found consistent evidence of a relationship between fall graduate enrollment and urbanization (and limited evidence differentiating between Carnegie Classification of highest, higher, and moderate research activity as well as fall undergraduate enrollment) with institutional average salary and proportions of assistant professors. Finally, I provided a detailed methodological procedure by which policy researchers can study policy implementations over multiple years.

Implications

This study had policy and practice implications for state policymakers and higher education administrators. These implications surround policy implementation and potential unintended consequences for policymakers and university administrators. Specific to university administrators are implementation considerations regarding shifting to an RCM budgeting environment.

Implications for Practice

This study had policy and practice implications for higher education administrators at the central and decentralized (college and department) levels broadly and for the engineering field, specifically. In RCM environments, funds should be distributed equitably through a process that recognizes “the diversity of institutions, programs and students” (Zierdt, 2009, p. 350). Policy implementation theory tells us that policies impact populations differently and in varying degrees. Disparate impact holds that employment discrimination occurred “when neutral policies or practices had a disproportionate, adverse impact on any protected class” (Equal Employment Opportunity Commission, n.d.), which includes women and racially minoritized persons. Therefore, it was critical to understand how RCM, as an institutional policy, impacted faculty in protected classes.

Although central administrators may find the results of this study reassuring that RCM models did not appear to negatively impact salaries or proportions by race/ethnicity of assistant professors on the tenure track, RCM models differ by institutions, although they share common core features. Therefore, administrators should interpret these findings cautiously, and conduct an internal study of their own RCM models to ensure inequalities across gender, race, ranks, and track do not persist at their institutions in light of formulaic differences or variations in decision-making across colleges and departments within their universities.

Similarly, although college deans and department heads might also find this study reassuring, they should also carefully examine their institution's RCM model to ensure inequalities do not persist at their institutions or for their colleges or departments. In light of the findings of my exploratory analysis of salaries of assistant professors of engineering between two public research universities in Ohio, engineering deans and department heads should especially be interested in examining faculty composition and compensation for inequities.

Future Research

The United States lacks a recent, comprehensive population level survey of faculty compensation complete with known predictors of faculty salaries. Although it is promising that I did not find any evidence associating RCM implementation with inequities in faculty salaries by gender or by gender and race/ethnicity, there were predictors of faculty compensation for which I was unable to account. I would expand the college-level exploratory data analysis of engineering assistant professors that I conducted because I found a noticeable, albeit not significant, difference in salaries by RCM implementation. I would expand data collection efforts at the college and department level, capturing faculty salary data at more ranks and tracks through online state and institutional websites, and expand the study to other institutions and states.

To better situate faculty compensation and faculty composition studies and isolate the policy effect of RCM, I would also like to identify characteristics that make an institution more likely to adopt RCM. Sector impacted time of RCM implementation, with RCM first being implemented by private institutions (Zierdt, 2009) and more recently increasing in popularity among public institutions (Jaquette et al., 2018). None of the institutions in my sample were unionized, so that is one institutional characteristic to further examine.

Future research might also expand the time period of this study, to better account for the increase in RCM at public universities prior to FY2012. Although faculty salary data may not be available in IPEDS for all years, other data sources might allow for a more robust longitudinal dataset that is better able to study RCM implementation over a longer time period. Future research might also incorporate a longer lag time for which to measure the change in trends for the outcome variable. For example, the impact of RCM implementation on tenured/tenure track faculty hiring, promotion, or salary increases may be longer than one to two-years because of the window of time needed for those processes to occur. A longer time period may be needed in which the policy effect to register.

The mean numbers of Nonresident Alien men and women were slightly higher or the same at RCM institutions than at non-RCM institutions (see Table 4.13) in my sample. In the 1990s, U.S. immigration laws changed, permitting more international doctorate holders to immigrate to the United States, and numbers of international faculty have continued to rise, especially at doctoral research universities (Kim, Twombly, & Wolf-Wendel, 2012). These international faculty are highly concentrated in science and engineering disciplines (Kim et al., 2012). Further research into the size and composition of the engineering departments at the RCM and non-RCM institutions within the institutional matched pairs for the sample might help to further explain this particular finding. Additionally, Gehl (2016) found some evidence that increased department head discretion influenced pay inequities for foreign-born STEM faculty. I would like to explore department head discretion and faculty proportions, including Nonresident

Alien faculty proportions comparing RCM and non-RCM environments. Future research might also explore the costs to universities and required procedure for employing international faculty.

Additional qualitative research is needed to determine how deans perceive RCM in relation to faculty composition and faculty compensation. Deans have increased budgetary power and responsibility under RCM models (Barr & McClellan, 2018; Whalen, 1991). This study was limited to the assistant professor rank, but expanding the analysis to an examination of the associate professor and full professor ranks might better capture deans' compensation decisions based on how they value, measure, and incentivize faculty productivity (i.e. extramural funding). Qualitative research is also needed to better understand their decision-making processes when allocating faculty lines, faculty salaries, and other forms of compensation. Qualitative data available from these deans would provide insight on *how* and *why* resources are distributed as they are, where this study provided insight on the outcomes of these distributions. Additionally, future research might draw from Argyris and Schön (1974)'s theory of action to determine if the *espoused* decision-making values of deans and department heads align with decision-making in practice in a RCM environment. Wall Bortz et al. (2020) recently applied this theory to a study of graduate program directors' recruiting and compensation practices for STEM doctoral students and revealed that in a competitive environment, program directors adopted non-evidence-based recruitment and compensation strategies that were incongruent with their stated values.

Additional qualitative research is needed to determine how faculty experience and perceive RCM in relation to faculty compensation processes and outcomes. Qualitative data from faculty who have experienced RCM implementation would shed light on *perceived* fairness of the RCM system and faculty compensation process. Equity theory, from which organizational justice theory was derived, tells us that employees evaluate pay in comparison to systems (Goodman, 1974); if employees feel pay inequities exist within a system, they will seek to reduce the inequity by reducing productivity or leaving the field (Adams, 1965; Lawler, 1971). RCM pushes revenue generation and cost containment to the college or departmental level (Strauss & Curry, 2002; Volpatti, 2013); therefore, deans or department heads, as leaders of responsibility centers, have a vested interest in faculty productivity under RCM.

Engineering deans and department heads have a vested interest in retaining engineering faculty, especially women and racially minoritized faculty who are underrepresented in engineering. In the highly competitive engineering environment that faces competition from industry for advanced engineering degree holders, qualitative data from faculty about compensation and their work environment would be beneficial. Qualitative data would provide insight into factors missing from this study that quantitative data are unable to ascertain, such as discrimination, microaggressions, and hostile climate, all factors that negatively impact faculty research productivity, which is also linked to faculty compensation and retention. There may be inequitable experiences of faculty labor not related to faculty composition or faculty compensation. For example, women have heavier teaching, mentoring, and service loads than men faculty and women and racially minoritized faculty experience greater amounts of gender and race-based microaggressions in academia (Egan & Garvey, 2015). Throughout their academic careers, Black women full professors consistently face gendered and racial microaggressions (Croom, 2017).

Conclusion

RCM implementation is associated with increased decentralized decision-making power and budgetary responsibility for college deans and department heads. My study provided very little evidence that RCM implementation is associated with inequitable outcomes in faculty composition and faculty compensation. However, my study had several limitations and caveats, and thus the findings should be interpreted with caution. RCM models vary among institutions, and differences at the college or department level after RCM implementation may not be visible at the institutional level. For example, there may be other explanations for not finding differences between RCM and non-RCM universities at the institutional level. In my study of IPEDS data, there may have been disciplinary differences, where faculty in one academic discipline were affected negatively but faculty in another academic discipline were affected positively. In my study of Engineering faculty compensation, the RCM may have if funding distributed different; new budget model might disproportionately allocate funding to certain academic colleges. In other words, there may have been inequities in faculty composition or compensation at the departmental or college level that were not apparent at the institutional level.

As RCM did not appear to be associated with any changes in faculty composition or compensation practices, I did not find any evidence that RCM implementation impacted the procedural justice (i.e., decision-making criteria and processes of deans or department heads) as determined through measures of distributive justice (i.e., salary amounts or proportions of who was hired by gender and race/ethnicity) of faculty composition or faculty compensation at public, doctoral universities. Although RCM offers the benefit of increased transparency (Pappone, 2016), faculty are often frustrated by a lack of transparency in compensation practices (Carson, 2013; Wallace & King, 2013). This study demonstrated that central and decentralized administrators alike should be aware of their own autonomy in decision-making process, criteria by which they make decisions, and environment within which they make those decisions (such as presence of an RCM model), as procedural justice theory demonstrates *how* faculty perceive compensation to be awarded matters as much as actual salaries earned.

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Appendices

Appendix A

Institutions in Sample Excluded from IPEDS Analysis

	University Name	Exclusion Criteria
1.	Air Force Institute of Technology-Graduate School of Engineering & Management	Unable to identify budget model
2.	Arizona State University-Downtown Phoenix	Substantial data missing in IPEDS
3.	Arizona State University-Skysong	Substantial data missing in IPEDS
4.	Augusta University	Substantial data missing in IPEDS
5.	Boise State University	Plans to implement RCM
6.	Central Michigan University	RCM Prior to 2012
7.	Cleveland State University	RCM Prior to 2012
8.	Florida International University	Plans to implement RCM
9.	Indiana University-Bloomington	RCM Prior to 2012
10.	Indiana University-Purdue University-Indianapolis	RCM Prior to 2012
11.	Iowa State University	RCM Prior to 2012
12.	Kansas State University	Plans to implement RCM
13.	Kennesaw State University	Doctoral Carnegie Classification 2016+
14.	Kent State University at Kent	RCM Prior to 2012
15.	Naval Postgraduate School	Missing IPEDS salary data 2013
16.	Ohio State University-Main Campus	RCM Prior to 2012
17.	Rutgers University-New Brunswick	RCM Prior to 2012
18.	Rutgers University-Newark	RCM Prior to 2012
19.	Texas A & M University-College Station	RCM Prior to 2012
20.	Texas A & M University-Commerce	RCM Prior to 2012
21.	Texas A & M University-Corpus Christi	RCM Prior to 2012
22.	Texas A & M University-Kingsville	RCM Prior to 2012
23.	The University of Alabama	Plans to implement RCM
24.	University of Alabama at Birmingham	Hybrid model
25.	University of California-Los Angeles	RCM Prior to 2012
26.	University of California-Merced	Not in Carnegie Universe until 2016
27.	University of Cincinnati	RCM Prior to 2012
28.	University of Delaware	RCM Prior to 2012
29.	University of Florida	RCM Prior to 2012
30.	University of Idaho	RCM Prior to 2012
31.	University of Illinois at Urbana-Champaign	RCM Prior to 2012
32.	University of Maryland-Eastern Shore	Doctoral Carnegie Classification 2015+
33.	University of Michigan-Ann Arbor	RCM Prior to 2012
34.	University of Minnesota-Twin Cities	RCM Prior to 2012
35.	University of New Hampshire-Main Campus	RCM Prior to 2012
36.	University of Oregon	RCM Prior to 2012
37.	University of Pittsburgh-Pittsburgh Campus	RCM Prior to 2012
38.	University of Puerto Rico-Rio Piedras	Unable to identify budget model
39.	University of Utah	RCM Prior to 2012
40.	Virginia Polytechnic Institute and State University	Plans to implement performance budgeting
41.	Wright State University	RCM Prior to 2012

Note. Years represent fiscal years. Ball State University was kept in sample as non-RCM institution as plans to implement RCM do not begin until 2021.

Appendix B

Universities in Control (Non-RCM) Group for IPEDS Data Analysis

1. Arizona State University-Tempe
2. Ball State University
3. Binghamton University
4. Bowling Green State University-Main Campus
5. California State University-Fresno
6. California State University-Fullerton
7. Clemson University
8. College of William and Mary
9. Colorado School of Mines
10. Colorado State University-Fort Collins
11. CUNY Graduate School and University Center
12. East Carolina University
13. East Tennessee State University
14. Eastern Michigan University
15. Florida Agricultural and Mechanical University
16. Florida Atlantic University
17. Florida State University
18. Georgia Institute of Technology-Main Campus
19. Georgia Southern University
20. Georgia State University
21. Idaho State University
22. Illinois State University
23. Indiana State University
24. Indiana University of Pennsylvania-Main Campus
25. Jackson State University
26. Lamar University
27. Louisiana State University and Agricultural & Mechanical College
28. Louisiana Tech University
29. Miami University-Oxford
30. Michigan State University
31. Michigan Technological University
32. Middle Tennessee State University
33. Mississippi State University
34. Missouri University of Science and Technology
35. Montana State University
36. Montclair State University
37. Morgan State University
38. New Jersey Institute of Technology
39. New Mexico State University-Main Campus
40. North Carolina A & T State University
41. North Carolina State University at Raleigh
42. North Dakota State University-Main Campus
43. Northern Arizona University
44. Northern Illinois University
45. Oakland University
46. Oklahoma State University-Main Campus
47. Old Dominion University
48. Oregon State University
49. Pennsylvania State University-Main Campus
50. Portland State University
51. Prairie View A & M University
52. Purdue University-Main Campus
53. Rowan University
54. Sam Houston State University
55. San Diego State University
56. San Francisco State University
57. South Dakota State University
58. Southern Illinois University-Carbondale
59. Stony Brook University
60. SUNY at Albany
61. SUNY College of Environmental Science and Forestry
62. Temple University
63. Tennessee State University
64. Tennessee Technological University
65. Texas Southern University
66. Texas State University
67. Texas Woman's University
68. The University of Montana
69. The University of Tennessee-Knoxville
70. The University of Texas at Arlington
71. The University of Texas at Austin
72. The University of Texas at Dallas
73. The University of Texas at El Paso
74. The University of Texas at San Antonio
75. The University of Texas Rio Grande Valley
76. The University of West Florida
77. University at Buffalo
78. University of Akron Main Campus

Appendix B

Universities in Control (Non-RCM) Group for IPEDS Data Analysis, continued

79. University of Alaska Fairbanks
80. University of Arkansas
81. University of Arkansas at Little Rock
82. University of California-Berkeley
83. University of California-Irvine
84. University of California-San Diego
85. University of California-Santa Barbara
86. University of California-Santa Cruz
87. University of Central Florida
88. University of Colorado Boulder
89. University of Colorado Denver/Anschutz Medical Campus
90. University of Connecticut
91. University of Georgia
92. University of Hawaii at Manoa
93. University of Houston
94. University of Illinois at Chicago
95. University of Iowa
96. University of Kansas
97. University of Kentucky
98. University of Louisiana at Lafayette
99. University of Louisiana at Monroe
100. University of Louisville
101. University of Maine
102. University of Maryland-Baltimore County
103. University of Maryland-College Park
104. University of Massachusetts-Amherst
105. University of Massachusetts-Boston
106. University of Massachusetts-Dartmouth
107. University of Massachusetts-Lowell
108. University of Memphis
109. University of Mississippi
110. University of Missouri-Columbia
111. University of Missouri-Kansas City
112. University of Missouri-St Louis
113. University of Nebraska at Omaha
114. University of Nebraska-Lincoln
115. University of Nevada-Las Vegas
116. University of Nevada-Reno
117. University of New Mexico-Main Campus
118. University of New Orleans
119. University of North Carolina at Chapel Hill
120. University of North Carolina at Charlotte
121. University of North Carolina at Greensboro
122. University of North Dakota
123. University of North Texas
124. University of Northern Colorado
125. University of Oklahoma-Norman Campus
126. University of Rhode Island
127. University of South Alabama
128. University of South Carolina-Columbia
129. University of South Dakota
130. University of South Florida-Main Campus
131. University of Southern Mississippi
132. University of Toledo
133. University of Vermont
134. University of Washington-Seattle Campus
135. University of West Georgia
136. University of Wisconsin-Madison
137. University of Wisconsin-Milwaukee
138. University of Wyoming
139. Utah State University
140. Valdosta State University
141. Virginia Commonwealth University
142. Washington State University
143. Wayne State University
144. West Virginia University
145. Western Michigan University
146. Wichita State University

Appendix C

Institutions in Sample Excluded from ASEE Data Analysis

University Name	Exclusion Criteria
1. Ball State University	Missing data from 2010-2019
2. Binghamton University	Duplicate, conflicting data in ASEE for 2015-2018
3. Bowling Green State University-Main Campus	Data available from 2018 only
4. College of William & Mary	Missing from ASEE
5. Colorado State University-Fort Collins	Missing from ASEE
6. CUNY Graduate School and University Center	Missing from ASEE
7. East Carolina University	Data available from 2010-2018 only
8. East Tennessee State University	Missing from ASEE
9. Eastern Michigan University	Data available from 2015-2018 only
10. Florida Agricultural and Mechanical University	Data available from 2018 only
11. Florida State University	Missing from ASEE
12. Georgia Southern University	Missing data from 2010 and 2019
13. Georgia State University	Missing from ASEE
14. Illinois State University	Missing from ASEE
15. Indiana State University	Missing from ASEE
16. Indiana University of Pennsylvania-Main Campus	Missing from ASEE
17. Jackson State University	Missing data from 2014-2016
18. Middle Tennessee State University	Data available from 2017-2018 only
19. Montclair State University	Missing from ASEE
20. Sam Houston State University	Missing from ASEE
21. SUNY at Albany	Missing from ASEE
22. Texas Southern University	Data available from 2015-2018 only
23. Texas State University	Missing from ASEE
24. Texas Woman's University	Missing from ASEE
25. The University of Montana	Missing from ASEE
26. University of Louisiana at Monroe	Missing from ASEE
27. University of Massachusetts-Boston	Data available from 2018 only
28. University of Missouri-St. Louis	Data available from 2018 only
29. University of Nebraska at Omaha	Missing from ASEE
30. University of North Carolina at Greensboro	Missing from ASEE
31. University of Northern Colorado	Missing from ASEE
32. University of South Dakota	Missing from ASEE
33. University of Southern Mississippi	Data available from 2013-2018 only
34. The University of Texas Rio Grande Valley	Data available from 2015-2018 only
35. University of West Florida	Data only available from 2018
36. University of West Georgia	Missing from ASEE
37. Valdosta State University	Missing from ASEE

Note. Years represent fiscal years. Binghamton University was named The State University of New York at Binghamton in ASEE Database.

Appendix D

Universities in Control (Non-RCM) Group for ASEE Data Analysis

1. Arizona State University-Tempe
2. California State University-Fresno
3. California State University-Fullerton
4. Clemson University
5. Colorado School of Mines
6. Florida Atlantic University
7. Georgia Institute of Technology-Main Campus
8. Idaho State University
9. Lamar University
10. Louisiana State University and Agricultural & Mechanical College
11. Louisiana Tech University
12. Miami University-Oxford
13. Michigan State University
14. Michigan Technological University
15. Mississippi State University
16. Missouri University of Science and Technology
17. Montana State University
18. Morgan State University
19. New Jersey Institute of Technology
20. New Mexico State University-Main Campus
21. North Carolina A & T State University
22. North Carolina State University at Raleigh
23. North Dakota State University-Main Campus
24. Northern Arizona University
25. Northern Illinois University
26. Oakland University
27. Oklahoma State University-Main Campus
28. Old Dominion University
29. Oregon State University
30. Pennsylvania State University-Main Campus
31. Portland State University
32. Prairie View A & M University
33. Purdue University-Main Campus
34. Rowan University
35. SUNY College of Environmental Science and Forestry
36. San Diego State University
37. San Francisco State University
38. South Dakota State University
39. Southern Illinois University-Carbondale
40. Stony Brook University
41. Temple University
42. Tennessee State University
43. Tennessee Technological University
44. The University of Tennessee-Knoxville
45. The University of Texas at Arlington
46. The University of Texas at Austin
47. The University of Texas at Dallas
48. The University of Texas at El Paso
49. The University of Texas at San Antonio
50. University at Buffalo
51. University of Akron Main Campus
52. University of Alaska Fairbanks
53. University of Arkansas
54. University of Arkansas at Little Rock
55. University of California-Berkeley
56. University of California-Irvine
57. University of California-San Diego
58. University of California-Santa Barbara
59. University of California-Santa Cruz
60. University of Central Florida
61. University of Colorado Boulder
62. University of Colorado Denver/Anschutz Medical Campus
63. University of Connecticut
64. University of Georgia
65. University of Hawaii at Manoa
66. University of Houston
67. University of Illinois at Chicago
68. University of Iowa
69. University of Kansas
70. University of Kentucky
71. University of Louisiana at Lafayette
72. University of Louisville
73. University of Maine
74. University of Maryland-Baltimore County

Appendix D

Universities in Control (Non-RCM) Group for ASEE Data Analysis, continued

75. University of Maryland-College Park
76. University of Massachusetts-Amherst
77. University of Massachusetts-Dartmouth
78. University of Massachusetts-Lowell
79. University of Memphis
80. University of Mississippi
81. University of Missouri-Columbia
82. University of Missouri-Kansas City
83. University of Nebraska-Lincoln
84. University of Nevada-Las Vegas
85. University of Nevada-Reno
86. University of New Mexico-Main Campus
87. University of New Orleans
88. University of North Carolina at Chapel Hill
89. University of North Carolina at Charlotte
90. University of North Dakota
91. University of North Texas
92. University of Oklahoma-Norman Campus
93. University of Rhode Island
94. University of South Alabama
95. University of South Carolina-Columbia
96. University of South Florida-Main Campus
97. University of Toledo
98. University of Vermont
99. University of Washington-Seattle Campus
100. University of Wisconsin-Madison
101. University of Wisconsin-Milwaukee
102. University of Wyoming
103. Utah State University
104. Virginia Commonwealth University
105. Washington State University
106. Wayne State University
107. West Virginia University
108. Western Michigan University
109. Wichita State University

Appendix E

Description of IPEDS Variables

Variable Name	Variable Description
Average salary for instructional staff equated to a 9-month contract (total, men, women)	FY2017 – FY2019: This is calculated by dividing the total salary outlays of full-time, non-medical, instructional staff - total equated to month contract by the number of full-time, non-medical, instructional staff. Instructional Staff - An occupational category that consists of the following two functions: 1) "Instruction" only and 2) "Instruction combined with research and/or public service."
Average weighted monthly salary (total, men, women)	FY2013 – FY2016: Weighted average salary per month of full-time, non-medical, instructional staff as of November 1. Weighted average salary per month = total salary outlays divided by the total number of months covered. Instructional Staff - An occupational category that consists of the following two functions: 1) "Instruction" only and 2) "Instruction combined with research and/or public service."
Average salary of full-time instructional staff (total, men, women)	FY2011 – FY2012: Salaries of full-time non-medical instructional staff equated to 9-month contract length. Instruction/research staff employed full time (as defined by the institution) whose major regular assignment is instruction, including those with released time for research. For the Faculty Salaries survey, this group includes faculty designated as "primarily instruction" and "instruction, combined with research and public service."
Gender	For gender, men and women were selected.
Race/Ethnicity:	A person may be counted in only one group. Developed in 1997 by the Office of Management and Budget (OMB) that are used to describe groups to which individuals belong, identify with, or belong in the eyes of the community. The categories do not denote scientific definitions of anthropological origins. The designations are used to categorize U.S. citizens, resident aliens, and other eligible non-citizens. Individuals are asked to first designate ethnicity as: a) Hispanic or Latino or b) Not Hispanic or Latino. Second, individuals are asked to indicate all races that apply among the following: a) American Indian or Alaska Native, b) Asian, c) Black or African American, d) Native Hawaiian or Other Pacific Islander, or e) White.
American Indian or Alaska Native	American Indian or Alaska Native - A person having origins in any of the original peoples of North and South America (including Central America) who maintains cultural identification through tribal affiliation or community attachment.
Asian	Asian - A person having origins in any of the original peoples of the Far East, Southeast Asia, or the Indian Subcontinent, including, for example, Cambodia, China, India, Japan, Korea, Malaysia, Pakistan, the Philippine Islands, Thailand, and Vietnam.
Black or African American	Black or African American - A person having origins in any of the black racial groups of Africa.
Hispanic or Latino	Hispanic or Latino - A person of Cuban, Mexican, Puerto Rican, South or Central American, or other Spanish culture or origin, regardless of race.

Appendix E

Description of IPEDS Variables, continued

Variable Name	Variable Description
Native Hawaiian or Other Pacific Islander	Native Hawaiian or Other Pacific Islanders - A person having origins in any of the original peoples of Hawaii, Guam, Samoa, or other Pacific Islands.
Nonresident Alien	A person who is not a citizen or national of the United States and who is in this country on a visa or temporary basis and does not have the right to remain indefinitely.
Race/Ethnicity Unknown	Category used to classify students or employees whose race/ethnicity is not known and institutions are unable to place them in one of the specified racial/ethnic categories.
Two or More Races	Two or more races - Category used by institutions to report persons who selected more than one race.
White	White - A person having origins in any of the original peoples of Europe, the Middle East, or North Africa.
Carnegie Classification – Doctoral Universities	FY2019: Carnegie Classification 2018: Basic. Doctoral universities - Includes institutions that awarded at least 20 research/scholarship doctoral degrees during the update year and also institutions with below 20 research/scholarship doctoral degrees that awarded at least 30 professional practice doctoral degrees in at least 2 programs. Excludes Special Focus Institutions and Tribal Colleges. The first two categories include only institutions that awarded at least 20 research/scholarship doctoral degrees and had at least $5 million in total research expenditures (as reported through the National Science Foundation (NSF) Higher Education Research & Development Survey (HERD)). R1: Doctoral Universities – Very high research activity. R2: Doctoral Universities – High research activity. D/PU: Doctoral/Professional Universities. FY2016 – FY2018: Carnegie Classification 2015: Basic. In the 2015 update, the categories of the Research Doctoral Universities changed (but not the calculation methodology). The "shorthand" labels for the Doctoral Universities were restored in the 2015 update to numeric sequences (R1, R2, R3) to denote differences in quantitative levels based on a research activity index. Doctoral Universities - Includes institutions that awarded at least 20 research/scholarship doctoral degrees during the update year (this does not include professional practice doctoral-level degrees, such as the JD, MD, PharmD, DPT, etc.). Excludes Special Focus Institutions and Tribal Colleges. FY2011 – FY2015: Carnegie Classification 2005/2010: Basic (2005-06 to 2014-15). Doctorate-granting Universities. Includes institutions that award at least 20 doctoral degrees per year (excluding doctoral-level degrees that qualify recipients for entry into professional practice, such as the JD, MD, PharmD, DPT, etc.) Excludes Special Focus Institutions and Tribal Colleges. RU/VH: Research Universities (very high research activity). RU/H: Research Universities (high research activity). DRU: Doctoral/Research Universities.

Appendix E

Description of IPEDS Variables, continued

Variable Name	Variable Description
Fall enrollment	Graduate: Total graduate men and women enrolled for credit in the fall of the academic year. Graduate student A student who holds a bachelor's or first-professional degree, or equivalent, and is taking courses at the post-baccalaureate level. These students may or may not be enrolled in graduate programs. Undergraduate: Total undergraduate men and women enrolled for credit in the fall of the academic year. Undergraduate - A student enrolled in a 4- or 5-year bachelor's degree program, an associate's degree program, or a vocational or technical program below the baccalaureate. Credit - Recognition of attendance or performance in an instructional activity (course or program) that can be applied by a recipient toward the requirements for a degree, diploma, certificate, or other formal award. Enrollment reported is of the institution's official fall reporting date or October 15.
Bureau of Economic Analysis (BEA) Regions	BEA Regions are a set of Geographic Areas that are aggregations of the states. The regional classifications, which were developed in the mid-1950s, are based on the homogeneity of the states in terms of economic characteristics, such as the industrial composition of the labor force, and in terms of demographic, social, and cultural characteristics. BEA groups all 50 states and the District of Columbia into eight distinct regions for purposes of data collecting and analyses. 0 - US Service schools 1 - New England CT ME MA NH RI VT 2 - Mid East DE DC MD NJ NY PA 3 - Great Lakes IL IN MI OH WI 4 - Plains IA KS MN MO NE ND SD 5 - Southeast AL AR FL GA KY LA MS NC SC TN VA WV 6 - Southwest AZ NM OK TX 7 - Rocky Mountains CO ID MT UT WY 8 - Far West AK CA HI NV OR WA 9 - Outlying areas AS FM GU MH MP PR PW VI -3 - Not available
Degree of urbanization	Degree of urbanization (Urban-centric locale). Locale codes identify the geographic status of a school on an urban continuum ranging from “large city” to “rural.” They are based on a school’s physical address. The urban-centric locale codes introduced in this file are assigned through a methodology developed by the U.S. Census Bureau’s Population Division in 2005. The urban-centric locale codes apply current geographic concepts to the original NCES locale codes used on IPEDS files through 2004. 11 - City: Large: Territory inside an urbanized area and inside a principal city with population of 250,000 or more. 12 - City: Midsize: Territory inside an urbanized area and inside a principal city with population less than 250,000 and greater than or equal to 100,000. 13 - City: Small: Territory inside an urbanized area and inside a principal city with population less than 100,000.

Appendix E

Description of IPEDS Variables, continued

Variable Name	Variable Description
Degree of urbanization, continued	21 - Suburb: Large: Territory outside a principal city and inside an urbanized area with population of 250,000 or more. 22 - Suburb: Midsize: Territory outside a principal city and inside an urbanized area with population less than 250,000 and greater than or equal to 100,000. 23 - Suburb: Small: Territory outside a principal city and inside an urbanized area with population less than 100,000. 31 - Town: Fringe: Territory inside an urban cluster that is less than or equal to 10 miles from an urbanized area. 32 - Town: Distant: Territory inside an urban cluster that is more than 10 miles and less than or equal to 35 miles from an urbanized area. 33 - Town: Remote: Territory inside an urban cluster that is more than 35 miles of an urbanized area. 41 - Rural: Fringe: Census-defined rural territory that is less than or equal to 5 miles from an urbanized area, as well as rural territory that is less than or equal to 2.5 miles from an urban cluster. 42 - Rural: Distant: Census-defined rural territory that is more than 5 miles but less than or equal to 25 miles from an urbanized area, as well as rural territory that is more than 2.5 miles but less than or equal to 10 miles from an urban cluster. 43 - Rural: Remote: Census-defined rural territory that is more than 25 miles from an urbanized area and is also more than 10 miles from an urban cluster.

Note. Variables were extracted from IPEDS. Salary and faculty demographic information was obtained from the salaries section of the Human Resource Component survey.

Appendix F

Description of Variables from American Society for Engineering Education (ASEE) Database

Variable Name	Variable Description
Assistant Professors	Number of engineering faculty at institution at the rank of assistant professor with tenure or on the tenure track.
Engineering	The full listing of engineering discipline categories includes: Aerospace Engineering, Agricultural Engineering, Architectural Engineering, Biomedical Engineering, Chemical Engineering, Civil Engineering, Computer Engineering, Computer Science (inside engineering), Computer Science (outside engineering), Electrical Engineering, Electrical/Computer Engineering, Engineering (general), Engineering Management, Engineering Science and Engineering, Physics, Environmental Engineering, Industrial/Manufacturing Engineering, Mechanical Engineering, Metallurgical and Materials Engineering, Mining Engineering, Nuclear Engineering, Petroleum Engineering, Other Engineering Disciplines
Gender	To compare gender, the dichotomous, categorical variables listed for biological sex were examined (male and female).
Race/Ethnicity:	
African American Faculty - Black or African American	A person having origins in any of the black racial groups of Africa. Terms such as “Haitian” or “Negro” can be used in addition to “Black or African American.”
Asian American Faculty – Asian	A person having origins in any of the original peoples of the Far East, Southesast Asia, or the Indian subcontinent including, for example, Cambodia, China, India, Japan, Korea, Malaysia, Pakistan, the Philippine Islands, Thailand, and Vietnam.
Hispanic Faculty - Hispanic or Latino	A person of Cuban, Mexican, Puerto Rican, South or Central American, or other Spanish culture or origin, regardless of race. The term, “Spanish origin,” can be used in addition to “Hispanic or Latino.” Hispanic/Latino includes individuals of any race who identify as Hispanic or Latino. The five race categories include only persons who reported one of those fields as their sole race and did not report Hispanic/Latino ethnicity.
Native American Faculty - American Indian or Alaska Native	A person having origins in any of the original peoples of North and South America (including Central America), and who maintains tribal affiliation or community attachment.
Native Hawaiian Faculty - Native Hawaiian or Other Pacific Islander	A person having origins in any of the original peoples of Hawaii, Guam, Samoa, or other Pacific Islands.

Appendix F

Description of Variables from American Society for Engineering Education (ASEE) Database

Variable Name	Variable Description
Nonresident Alien	A person who is not a citizen or a national of the United States and who is in this country on a visa or temporary basis and does not have the right to remain indefinitely. Nonresident aliens should not be included in any of the race or ethnicity fields.
Two or More	Any person who reported themselves as belonging to more than one of the race categories. These individuals should only be counted in this field and not any of the race categories.
Caucasian Faculty - White	A person having origins in any of the original peoples of Europe, the, Middle, East, or North Africa.

Note. Variables and descriptions were obtained from ASEE. Race/ethnicity descriptions were based on federal guidelines.

Appendix G

Comparison of University RCM Model Revenue Allocations

University	Undergraduate	Graduate	Sponsored Activity
Auburn University (2014)[a]	Tuition: 70% instruction 30% major State Appropriations: 70% to support resident instruction	Tuition: 100% major	100% Indirect Cost Recovery 30% of State Appropriations to support sponsored programs
George Mason University (2017)[b]	Tuition: 80% instruction 20% major (Less window 13-16 SCH, special programs) State Appropriations: 80% in-state instruction 20% in-state major	Tuition: 80% instruction 20% major State Appropriations: 80% in-state instruction 20% in-state major	
Ohio University (2014)[c]	Tuition: 85% instruction 15% major (3-year averages)	Tuition: 100% major	
University of Arizona (2016)[d]	Tuition: 75% instruction 25% majors	Tuition: 75% major 25% instruction	100% of Facilities & Administrative Recovery
University of California – Davis (2016)[e] University of California – Riverside (2016)[f]	Tuition: 70% to college 60% instruction 30% majors 10% degrees awarded	Tuition: 30% to college 100% major	
University of Virginia – Main Campus (2015)[g]	Tuition: 75% instruction 25% majors	Tuition: 100% major	

Note. Fiscal year of RCM Implementation in parentheses. Revenue allocations to colleges shown. Financial aid was subtracted from gross tuition before accounting for revenue from undergraduate and graduate tuition. Instruction was typically measured by student credit hours (SCH) within college of instruction. Unable to identify allocations for Texas Tech University (2012).

[a] https://www.auburn.edu/academic/provost/Strategic%20Budget%20Initiative/proposedmodel.html
[a] http://www.auburn.edu/administration/business-finance/pdf/17-18_consolidated.pdf
[b] https://svp.gmu.edu/wp-content/uploads/2017/02/Mason-Incentive-Model.pdf
[c] https://www.ohio.edu/sites/default/files/sites/finance/budget/files/bpc/bpc-materials-meeting-3.pdf
[d] https://rcm.arizona.edu/
[e] https://financeandbusiness.ucdavis.edu/bia/budget/process/model-alloc
[f] https://www.engr.ucr.edu/sites/g/files/rcwecm621/files/2018-02/bcoetalk.pdf
[g] https://financialmodel.virginia.edu/relevant-documentation