

## **ABSTRACT**

Title of Dissertation: AN ANALYSIS OF THE EFFECTS OF RESPONSIBILITY CENTER MANAGEMENT ON COSTS AT TWO PUBLIC RESEARCH UNIVERSITIES IN THE UNITED STATES: A SYNTHETIC CONTROL APPROACH

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This study examines the effect of responsibility center management (RCM), a decentralized budget model, on total operating costs at the University of New Hampshire (UNH) and the University of Arizona (UofA). Both universities in the study implemented RCM with the primary goal of controlling costs, among other goals. To address the research question, this study draws from extant literature on RCM and higher education cost and is theoretically framed using the principal-agent theory and the revenue theory of cost. The synthetic control method (SCM) – an econometric technique used to estimate the causal effects of policies, programs, interventions, and idiosyncratic events – is employed to conduct the analysis. The main findings of the study indicate that RCM positively impacted total operating costs at UNH and the UofA. However, with regard to UNH, further analysis did not reveal a significant causal effect with respect to RCM's impact on total operating costs. Additionally, as it relates to the UofA, the results revealed that RCM had a significant causal effect on total operating costs after the first year of implementation but not thereafter.

The findings of this study contribute to research and practice. With regard to research, this study is the first to bridge the gap between the RCM literature and the higher education cost literature by providing empirical insight regarding RCM's effect on total operating costs. Additionally, this study contributes to the use of theory in the RCM literature by using two theoretical frameworks to guide the inquiry. As it relates to practice, the results of this study – specifically that RCM positively impacted total operating costs – balance previous anecdotal claims regarding RCM's utility by providing empirical insight on RCM at UNH and UofA to guide future decision-making.

This study outlines several recommendations for future research to further develop empirical studies on RCM. Specifically, the study recommends the use of mixed methodologies to elucidate a fuller picture of RCM and ultimately help university leaders develop specific recommendations for policy and practice around resource allocation.

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MANAGEMENT ON COSTS AT TWO PUBLIC RESEARCH UNIVERSITIES  
IN THE UNITED STATES: A SYNTHETIC CONTROL APPROACH

by

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## Table of Contents

Acknowledgements.....	ii
Table of Contents.....	vii
List of Tables.....	x
List of Figures.....	xii
Chapter 1: Introduction.....	1
Introduction.....	1
Background and Context.....	2
State Funding Declines.....	2
Escalating Higher Education Costs.....	3
Rising Tuition Prices.....	4
An Overview of RCM.....	6
Summary of the Literature.....	15
Summary of the Literature on RCM.....	15
Summary of the Literature on Higher Education Costs.....	18
Statement of the Problem.....	21
Purpose of the Study.....	22
Summary of the Research Design.....	22
Summary of the Methodological Approach.....	22
Summary Descriptions of the Institutions in the Study.....	26
Summary of the Theoretical Frameworks.....	31
Description of the Data and Variables.....	32
Sample Period.....	34
Limitations.....	35
Significance of the Study.....	37
Summary of the Results.....	37
Summary of the Contributions to Research.....	37
Summary of the Contributions to Practice.....	38
Chapter 2: Literature Review.....	39
Introduction.....	39
Scholarship on RCM.....	40

Empirical Literature on RCM .....	40
Summary of Scholarship on RCM .....	59
Scholarship on Higher Education Costs .....	60
Theoretical Perspectives on Costs in Higher Education .....	60
Empirical Literature on Higher Education Costs .....	74
Summary of Scholarship on Higher Education Costs .....	92
Gaps and Limitations of Prior Research .....	93
Summary of the Research Gap .....	93
Methodological Limitations in the RCM Literature .....	93
Methodological Limitations in Higher Education Cost Literature .....	98
The Dearth of Theoretical Perspectives on RCM .....	99
Addressing the Gaps and Limitations of Prior Research .....	101
Theoretical Framework .....	101
Addressing the Methodological Limitations of Previous Research .....	107
Chapter Summary .....	114
Chapter 3: Methodology .....	115
Introduction .....	115
Research Design .....	115
Overview of Synthetic Control Methodology .....	115
Methodological Approach in Context .....	133
Theoretical Framework .....	133
Sample Selection .....	134
Data and Variables .....	135
Procedure .....	136
Limitations .....	140
Chapter 4: Results .....	143
Introduction .....	143
Findings .....	143
University of New Hampshire .....	143
University of Arizona .....	162
Summary of Results .....	181

Chapter 5: Discussion and Recommendations.....	183
Introduction.....	183
Discussion.....	184
University of New Hampshire .....	184
University of Arizona .....	188
Discussion of the Findings in the Context of Extant Literature.....	191
Contributions to Research.....	192
Contributions to Practice.....	197
Implications.....	198
Recommendations for Future Research .....	201
Appendix A.....	206
Sensitivity Analysis (Leave-one-out Test Results).....	212
References.....	220

## List of Tables

Table 4.1A: Descriptive Statistics: University of New Hampshire (Pre-treatment).....	147
Table 4.1B: Descriptive Statistics: University of New Hampshire (Treatment and Post-treatment).....	148
Table 4.2: Synthetic Control Unit for University of New Hampshire.....	150
Table 4.3: University of New Hampshire Pre-treatment Estimates.....	153
Table 4.4: Treatment Effects of RCM’s Impact on Operating Cost at University of New Hampshire.....	157
Table 4.5A: Descriptive Statistics: University of Arizona (Pre-treatment).....	166
Table 4.5B: Descriptive Statistics: University of Arizona (Treatment and Post-treatment Periods).....	167
Table 4.6: Synthetic Control Unit for University of Arizona.....	169
Table 4.7: University of Arizona Pre-treatment Estimates.....	172
Table 4.8: Treatment Effects of RCM’s Impact on Operating Cost at University of Arizona.....	177
Table A1: Public Universities in the US that have Implemented RCM.....	206
Table A2: Overview of RCM Operations at Institutions in the Study.....	207
Table A3: Data and Variables in the Study.....	209
Table B1: Synthetic Control Unit for University of New Hampshire (Synthetic UNH with University of Vermont Removed).....	212
Table B2: Pre-treatment Estimates for University of New Hampshire (Synthetic UNH with University of Vermont Removed).....	212
Table B3: Treatment Effects of RCM’s Impact on Operating Cost at University of New Hampshire (Leave-one-out Test).....	215
Table B4: Synthetic Control Unit for University of Arizona (Synthetic UofA with University of Georgia Removed).....	215

Table B5: Pre-treatment Estimates for University of Arizona (Synthetic UofA with University of Georgia Removed).....	216
Table B6: Treatment Effects of RCM’s Impact on Operating Cost at University of Arizona (Leave-one-out Test).....	219

## List of Figures

Figure 4.1: Graph of Treatment Effects of RCM’s Impact on Operating Cost at University of New Hampshire.....	157
Figure 4.2: Graph of Treatment Effects of RCM’s Impact on Operating Cost at University of Arizona.....	176
Figure A1: A Simple Example of SCM.....	211
Figure B1: Graph of Treatment Effects of RCM’s Impact on Operating Cost at University of New Hampshire (Leave-one-out Test).....	214
Figure B2: Graph of Treatment Effects of RCM’s Impact on Operating Cost at University of Arizona (Leave-one-out Test).....	219

## **Chapter 1: Introduction**

### **Introduction**

The ever-changing financial landscape of public higher education has challenged many college and university operations as it relates to securing funding (i.e., how and from where institutions receive and generate revenue) (Jaquette & Curs, 2015; Priest & St. John, 2006; Slaughter & Rhoades, 2004) and managing costs (i.e., the cost of providing higher education) (Robst, 2001; Sav, 2004; Titus, Vamosiu, & McClure, 2017; Toutkoushian, 1999). As a consequence, several public universities have sought and implemented strategies to manage and adapt to this financial environment. One such strategy called Responsibility Center Management (RCM) – also known as responsibility center budgeting, incentive-based budgeting, and revenue center budgeting – is a decentralized budget system and management tool that has been endorsed by its adopters as a way to manage complex university finances and strategic planning (Curry, Laws, & Strauss, 2013; Strauss & Curry, 2002; Whalen, 1991). Since the 1970s, over 45 universities have fully implemented RCM (Curry et al., 2013). Moreover, since the Great Recession in 2008, more than 25 public research universities have adopted RCM (see Table A1).

Given the ongoing challenges in public higher education regarding declining state financial support, escalating costs, and rising tuition prices, universities have employed RCM practices to achieve at least two broad goals: (1) to increase revenue, and (2) to minimize costs (Curry et al., 2013; Deering & Sá, 2014; Hanover Research Council, 2008; Jaquette, Kramer, & Curs, 2018; Strauss & Curry, 2002; Whalen, 1991). However, empirical research examining RCM, specifically the impact of RCM on revenue and



costs is scant. Only one study (Jaquette, Kramer, & Curs, 2018) examined the extent to which RCM impacted revenue – specifically, tuition revenue at four public research universities. No research has considered if or to what extent RCM affects costs, despite a dramatic increase in the number of RCM adopters since the Great Recession in 2008. This study aimed to fill that gap in knowledge and to help inform administrators and state policymakers who may be considering RCM for their institutions.

This study contributes to the literature by bridging the gap between RCM and higher education costs. Specifically, this study provides insight into RCM’s impact on costs at two public research universities in the United States: the University of New Hampshire (UNH) and the University of Arizona (UofA). The UNH and UofA, like many other public research universities, experienced significant declines in state funding and grappled with rising higher education costs. As a consequence, the leaders of UNH and UofA adopted RCM citing that their motivation to implement RCM was to incentivize cost minimization, among other goals. This study found that RCM positively impacted total operating costs at UNH and the UofA, however, causal evidence is not revealed for UNH, and is only revealed across one year of RCM implementation at UofA.

## **Background and Context**

### **State Funding Declines**

Over the last three decades, public colleges and universities have experienced significant changes in their funding streams as a result of declining state financial support (Baum & Ma, 2012; Doyle & Delany, 2011; Layzell, 2007; SHEEO, 2018). These statewide funding declines are a result of nationwide downturns in the economy during

the early 1990s, early and mid-2000s, including the Great Recession in 2008, that negatively impacted tax revenues collected by state governments. Consequently, states have had fewer financial resources to allocate across competing budgetary priorities (including higher education), leaving officials with difficult choices (Harris & Shadunsky, 2013). For example, in 1995, the average state appropriations to higher education accounted for nearly 13% of the states' general budgets but fell to less than 10% by fiscal year 2017 (SHEEO, 2018). Additionally, on a per-student basis, state appropriations decreased by nearly 30% over the last 30 years at public universities (McFarland et al., 2018). Indeed, state appropriations per FTE in 2019 remained nearly 2.4% below 2009 funding levels (SHEEO, 2020). Mitchell, Palacios, and Leachman (2015) noted that the “deep state funding cuts have major consequences for public colleges and universities” (p. 2). Specifically, these funding cuts to public higher education have had implications with regard to how universities budget and allocate resources.

### **Escalating Higher Education Costs**

In addition to decreases in state financial support, higher education costs (i.e., the cost of providing higher education) have continued to rise. For example, public colleges and universities have continued to spend more to provide higher education each year. Desrochers and Hurlburt (2014) showed that the direct and indirect costs on a per full-time equivalent (FTE) student basis increased dramatically at public research universities between 2003 and 2013. On the direct cost side, for example, spending on instruction increased by nearly 11% (Desrochers & Hurlburt, 2014). Instruction expenses include faculty and staff salaries, fringe benefits, supplies, and equipment (Desrochers &

Hurlburt, 2014). On the indirect cost side, per-FTE spending increased in several categories: on student services by 30%, on academic support by 25%, and on institutional support by 11.1% (Desrochers & Hurlburt, 2014). Student services expenses include non-instructional services such as admissions, financial aid administration, career counseling, and student organizations, for example. Academic support costs include non-instructional expenses such as library resources, museums, deans' offices and staff, and academic computing. Institutional support costs include expenditures on executive management, general administrative services, public relations, and fiscal operations (Desrochers & Hurlburt, 2014).

Rising costs coupled with declining state support has left public colleges and universities with at least three options: increase tuition price, cut costs, or both (Mitchell et al., 2015). Many public institutions have attempted to do one or both – that is, raise tuition prices and implement ways to cut costs.

### **Rising Tuition Prices**

With regard to tuition, between academic years 1988-89 and 2018-19, the average published tuition and fee prices (also known as “sticker price”) at public four-year universities grew from \$3,360 to \$10,230 (in 2018 dollars) (Ma, Baum, Pender, & Libassi, 2018). Additionally, the average net tuition and fee prices (i.e., what students actually pay) increased from \$1,870 in 1998-99 to \$3,740 in 2018-19 (in 2018 dollars) (Ma et al., 2018). Student fees also increased by 95% between 1999 and 2012 at public colleges and universities (McFarland et al., 2018).

Although tuition and fee pricing strategies have proved successful (as it relates to institutional finances), it shifted more higher education costs to students and families (Ma

et al., 2018; Sav, 2017; SHEEO, 2018; Webber, 2017). In a study on the relationship between FTE-state appropriations and net tuition paid by students, Webber (2017) found that for every \$1,000 decrease in FTE-state appropriations, the average student pays \$257 more per year. These financial changes (i.e., rising costs and rising tuition prices) have prompted public outcry (Heller, 2001; Zumeta, Brenneman, Callan, & Finney, 2012). Consequently, state legislators have called for greater accountability and cost efficiency among all public colleges and universities (Heller, 2001; Massy & Zemsky, 1990; Sav, 2017; Zumeta, 2001; Zumeta et al., 2012).

Given the changing financial circumstances of public higher education, at least two empirical studies (Deering & Sá, 2014; Jaquette et al., 2018) and several non-empirical publications (Curry et al., 2013; Strauss & Curry, 2002; Whalen, 1991) have argued that RCM has been adopted primarily as a means to increase revenues and decrease (or control) costs. Among public research universities specifically, RCM has been adopted in reaction to declining state appropriations to higher education (Deering & Sá, 2014; Jaquette et al., 2018; Lang, 2002). Since the Great Recession in 2008, over 25 public universities have implemented RCM as illustrated in Table A1 (Attis, Rosch, Jenkins, & Ho, 2016; Balough & Logue, 2013; Green, Jaschik, & Lederman, 2011; Hearn, Lewis, Kallsen, Holdsworth, & Jones, 2006; Jaquette et al., 2018; West, Seidita, DiMattia, & Whalen, 1997). However, despite the recent attraction toward RCM, the impact and performance of RCM with regard to cost remains unexplored. This study fills the gap regarding RCM's effect on costs.

## **An Overview of RCM**

Responsibility center management (RCM) was introduced into higher education by the University of Pennsylvania (UPenn) in 1974. RCM, as implemented by UPenn (and subsequently several other institutions), consists of a sharing of financial responsibility between central administration (i.e., offices of the president, provost, or vice presidents), and the leader of each respective responsibility center (e.g., the colleges and schools within the university). Specifically, under RCM, the sharing of financial responsibility is brokered using funding formulas and allocation rules allowing responsibility centers (i.e., colleges and schools) to generate revenues to pay for their expenses. These funding formulas also allow central administrators to steer the university in achieving its mission. Specifically, central administrators allocate funds responsibility centers to incent the achievement of mission-critical goals and objectives (Curry et al., 2013; Whalen, 1991). (A more robust description of RCM funding formulas, including a discussion on how RCM is structured and executed, is discussed below.)

Several RCM publications (e.g., Curry et al., 2013; Strauss & Curry, 2002; Whalen, 1991) have suggested that RCM is an effective tool for managing complex university finances and increasing efficiency. Specifically, Curry et al. (2013), Strauss and Curry (2002), and Whalen (1991) attribute RCM's success to at least two key features: the decentralization of budget authority; and the embedded incentives within RCM to promote financial responsibility.

### ***Decentralization of Budget Authority***

Prior to the implementation of RCM, most colleges and universities employed a central budgeting system, known as incremental budgeting (Curry et al., 2013; Goldstein,

2005, 2012; Hearn et al., 2006; Jaquette et al., 2018; Vonasek, 2011; Whalen, 1991).

Under the incremental budget model, central administrators maintained complete budget authority (i.e., complete discretion over budget allocation decisions). However, under the RCM budget model, budget authority is devolved from central administration to the responsibility centers. Specifically, this is done by dividing the university into one of three parts: (1) as a responsibility center; (2) as a part of central administration; or (3) as a support center (sometimes referred to as cost centers) (Curry et al., 2013; Goldstein, 2005, 2012; Hearn et al., 2006; Jaquette et al., 2018; Vonasek, 2011; Whalen, 1991).

***Responsibility Centers.*** In most RCM models, the academic units (e.g., schools, colleges, and departments) and some self-supporting auxiliaries (i.e., revenue-generating operations such as residential halls, dining services, and bookstores) are designated as responsibility centers. The heads of responsibility centers, typically deans, are responsible for generating revenue to pay for the direct and indirect expenses of their college or school's operations. For example, revenues to the university come from several sources including state appropriations, tuition and fees, research grants, federal and state contracts, private gifts, and auxiliary enterprises (e.g., self-supporting activities such as residence halls, student unions, bookstores, and dining services). In academic responsibility centers, revenues are driven by student enrollment. For example, some RCM *funding formulas* (i.e., revenue attribution and cost allocation guidelines) allocate all or some of the tuition dollars generated from student enrollment to the academic unit (i.e., responsibility center) that houses the student's major. The remaining tuition dollars are allocated to the academic units that provide instruction to students but are outside of their home college or school. For example, if a student's major is in the Business School,

a percentage of his/her/their tuition dollars will be allocated to the Business School. However, if the student takes a course in the history department, a portion of the student's tuition dollars will be allocated to the college that houses the history department (e.g., College of Humanities). (Further description regarding revenue allocations is below.)

Under RCM, deans are also encouraged to find other opportunities to generate revenue such as research grants and alumni giving. These funds could be used at the discretion of the responsibility centers to enhance their academic programs, recruit faculty/staff, support students, and pay for their colleges' direct and indirect expenses. However, a portion of all additional revenues generated by responsibility centers are subject to taxation by central administration (further described below). These tax funds are used to pay for overhead costs (indirect expenses) incurred by the responsibility centers and support centers (e.g., non-instructional units such as the office of financial aid, registrar's office, and student affairs). Indirect expenses are expenses that are incurred by the support centers for providing non-instructional services to students such as student support services, counseling, financial aid, information technology, and student activities. Direct expenses come from faculty and staff salaries, fringe benefits, supplies, equipment, and travel.

Because RCM provides deans with financial authority over revenues, direct-, and indirect expenses, proponents of RCM argue that deans are thereby incentivized to maximize profits and minimize costs (Curry et al., 2013; Strauss & Curry, 2002; Whalen, 1991). These RCM incentives will be described further below.

***Central Administration.*** Central administration typically refers to the offices of the president, provost, and chief financial officer. Under the RCM model, the primary responsibility for central administration is to ensure that the responsibility centers and support centers move in the direction that central administration intends (i.e., in achieving the university's mission and strategic objectives). This is accomplished through the use of funding incentives around revenue attribution and cost allocation. For example, as noted previously, revenues to the university come from several sources including state appropriations, tuition and fees, research grants, federal and state contracts, private gifts, and auxiliary enterprises (e.g., self-supporting activities such as residence halls, student unions, bookstores, and dining services). Under the RCM model, the central administration imposes a tax on all revenues generated by the responsibility centers. The "tax" imposed and collected by the central administration is called *participation*. These taxes are collected and then placed into a fund called the *subvention pool*. The subvention pool is used to steer the institution by (1) covering any overhead costs incurred by central administration, responsibility centers, and the support centers (e.g., non-instructional units such as the office of financial aid, registrar's office, student activities, etc.); (2) providing funding for responsibility centers that may be experiencing financial shortfalls; and (3) creating incentives around institutional goals and priorities (Curry et al., 2013; Hearn et al., 2006; Strauss & Curry, 2002).

For example, with regard to institutional goals, if a university sought to increase research production while using RCM as a budget model, the institution may develop incentives around research grants. The guidelines of revenue allocation would be negotiated by the central administration, deans, and faculty. For example, an institution



may operate under the rule that all research grant revenues be divided among the central administration, responsibility center, and the principal investigator (PI) (i.e., the faculty member who awarded the grant). Specifically, this means that a portion of a research grant is taxed and allocated to the central administration (e.g., the Vice President of Research's Office) to cover any overhead expenses for grant administration. Another portion of the research grant may be allocated to the responsibility center (i.e., a college or school) in which the PI's department is located. Finally, the remaining portion of the research grant would be allocated to the PI to conduct research, hire research staff, and/or buy supplies and equipment. Critical in the above example is an illustration of how the taxation system would work to cover the overhead expenses of a support center (e.g., the Vice President of Research's Office) based on revenue generated through non-enrollment means (i.e., through external research grants). Support centers will be described next.

***Support Centers.*** Under an RCM model, support centers are typically non-instructional administrative units such as the office of research, the office of information technology, student counseling, and support services, academic advising, admissions, and financial aid. Although support centers do not provide instruction to students, these centers still incur expenses to provide services to students. Salaries and benefits, equipment, and supplies are among some of their expenses. However, because support centers are non-revenue generating units, their expenses are paid for by central administration using the subvention pool, which is funded, in part, by the responsibility centers. This illustrates that RCM works in a system to fund the university's operations.

***Embedded Incentives in RCM***

The use of funding formulas and allocation rules in RCM provides responsibility center leaders with the structure, information, and incentives necessary to generate revenues and minimize costs within their units (Curry et al., 2013; Hanover Research Council, 2008; Lang, 2002; Leslie & Slaughter, 1997; Rutherford & Rabovsky, 2017; Whalen, 1991). In a scholarly paper describing the ways in which universities are changing their management structures, Leslie and Slaughter (1997) noted that “getting incentives and disincentives right will mean the devolution of budgets so that units are stimulated to increase competitive revenue and to control their expenditures” (p. 249).

**Generate Additional Revenue.** On the revenue side, RCM funding formulas determine how revenue sources are allocated to responsibility centers to cover the expenses of their activities. For example, under RCM, tuition and fee revenues typically flow directly to the academic units and are generated by student enrollment (Curry et al., 2013; Hanover Research Council, 2008; Hearn et al., 2006; Jaquette et al., 2018; Lang, 2002; Whalen, 1991). Specifically, revenues are allocated to responsibility centers in at least three ways: based on student credit hours (SCH), based on program enrollment, and based on graduation rates (i.e., completion rates) (Attis et al., 2016; Balough & Logue, 2013; Curry et al., 2013; Jaquette et al., 2018; Vonasek, 2011; Whalen, 1991).

Under an RCM model, each of these bases for revenue allocation incentivizes revenue growth differently. For example, revenue allocation based on SCH incentivizes course enrollment. Specifically, as course enrollment increases, the amount of tuition revenue allocated to the department teaching the course increases. Additionally, revenue allocation based on academic program enrollment incentivizes enrollment in specific academic majors. For example, as the number of students majoring in education

increases, the amount of tuition revenue allocated to the College of Education increases. Lastly, revenue allocation based on graduation rates incentivizes higher graduation rates. Specifically, central administration may provide more revenue to academic units that have increased the graduation rates in their programs (Attis et al., 2016; Balough & Logue, 2013; Curry et al., 2013; Vonasek, 2011).

These allocation rules differ by institution and revenue source (e.g., state appropriations are allocated differently than undergraduate tuition and fees). For example, in a consulting report on RCM implementation, Attis et al. (2016) illustrate that three major forms of revenue (e.g., undergraduate tuition revenue, graduate tuition revenue, and state appropriations) are allocated differently. For example, undergraduate revenue is allocated to responsibility centers at Iowa State University in a 75/25 fashion. This means that 75% of revenue is allocated based on SCH and the remaining 25% is allocated based on program enrollment. Undergraduate tuition revenue at the University of Michigan is allocated in a 50/50 fashion (i.e., it is split based on SCH and program enrollment). Additionally, undergraduate tuition revenue at the University of Minnesota is divided in a 25/75 way – with 25% of revenue allocated based on SCH and 75% based on program enrollment. This suggests that deans are encouraged to increase student enrollment (and revenue by extension) by enhancing their academic programs and course offerings to entice students to enroll. However, researchers have not yet considered the extent to which enrollment is affected by the implementation of RCM.

As noted previously, the revenues generated by responsibility centers are subject to a tax imposed by the central administration. However, after a responsibility center's direct and indirect expenses are paid, deans are allowed to carry over unused funds year-

to-year. This practice is a departure from the centralized incremental budgeting system. Specifically, under the centralized budget system, all unexpended funds are required to be sent back to central administration, and in some cases back to a state's budget office (Whalen, 1991).

RCM also permits deans to reallocate unexpended funds, so long as they spend those funds within the parameters of university policy (Curry et al., 2013; Whalen, 1991). These incentives (i.e., the ability to carryover and reallocate unexpended funds), in theory, allow deans to plan for future expenses, including recruiting new faculty and staff, enhancing the quality of their academic programs, as well as planning for future budgetary shortfalls.

Only one empirical study (Jaquette et al., 2018) has investigated RCM's effect on revenue – specifically tuition revenue. The scholars found that three of the four public research universities in their study increased tuition revenue after RCM had been implemented. This study (Jaquette et al., 2018) will be discussed in more detail below and in *Chapter 2: Literature Review*.

**Cost Minimization.** RCM additionally contains cost-minimization incentives. As stated above, deans are allowed to carry forward unused funds year over year. This incentive also has implications for costs – specifically, unexpended funds could be a result of cost-savings, which in theory creates an additional incentive for responsibility center leaders to be cost-conscious and perhaps frugal.

A second RCM cost minimization incentive provides responsibility center leaders (i.e., deans) with information on the full costs (i.e., direct costs and indirect costs) of their activities (i.e., academic programs, research, and service) (Curry et al., 2013; Hanover

Research Council, 2008; Jaquette et al., 2018; Strauss & Curry, 2002; Whalen, 1991). In their text on RCM, Curry et al. (2013) note that deans were limited in their ability to make prudent academic and financial decisions prior to the creation of RCM.

Specifically, Curry et al. (2013) argue that deans were not incentivized to understand the full costs associated with academic programs, including the cost of non-instructional services. Under RCM, however, as described above, deans (responsibility centers) are not only required to understand the full costs of their activities, but they are also required to pay for their college's activities – both direct- and indirect costs.

For example, on the direct cost side, if a college (i.e., a responsibility center) expects to realize an increase in income and enrollment, then the dean or department chair may be inclined to hire additional faculty and open more course sections to meet the demand. Conversely, if a responsibility center expects a budget shortfall or a decrease in enrollment, then the dean or department chair might be inclined to scale back and reduce the number of sections, adjunct faculty, and teaching assistants (Curry et al., 2013).

Additionally, on the indirect costs side (i.e., the costs associated with non-instructional support), there are various ways that promote cost minimization. For example, Attis et al. (2016) list 10 different indirect costs that some universities use in their RCM models. These indirect costs can be allocated to responsibility centers based on FTE students, FTE faculty, FTE staff, net assignable square footage (i.e., the building space occupied by the unit), and the share of student credit hours taught in the unit.

The bases for allocating indirect costs, similar to how revenues are allocated, incentivize cost minimization in different ways (Attis et al., 2016; Curry et al., 2013; Whalen, 1991). For example, indirect cost allocation based on net assignable square

footage incentivizes the efficient use of office and classroom space; whereas, cost allocation based on the shares of student, faculty, and staff FTEs promotes equity among responsibility centers based on a unit's size. Under this cost allocation rule, smaller units would not have to pay a higher share of expenses than larger units, for example. These cost allocation rules and incentives vary across institutions, however. As will be described in the next section, researchers have not yet considered the effect of RCM on costs. This study addresses that gap in the literature.

### **Summary of the Literature**

This study draws from two literature domains (i.e., the literature on RCM and literature on costs in higher education) to provide context around the topic and address the research question.

#### **Summary of the Literature on RCM**

The scholarly literature on RCM is scant and disconnected from any systematic investigation on RCM's impact on the institutions that have implemented it. Specifically, scholars have mostly examined RCM using qualitative case study research designs. As a consequence, most research findings on RCM are institution- and context-specific (i.e., not generalizable). Additionally, as a consequence, the extant literature has only revealed two broad findings regarding RCM: (1) colleges and universities have primarily implemented RCM to enhance their financial positions (i.e., to generate additional revenue and minimize costs) (Deering & Sá, 2014; Jaquette et al., 2018); and (2) many institutions that use RCM have realized positive and negative experiences regarding

RCM's implementation and operation (Courant & Knepp, 2002; Deering & Sá, 2018; Gros Louis & Thompson, 2002; Hearn et al., 2006; Lang, 2002).

Colleges and universities have used RCM to improve their financial positions. For example, Jaquette et al. (2018) explored RCM at four public research universities: to identify why the administrators at each of these institutions sought to implement RCM; and to reveal the extent to which RCM impacted tuition revenue. Jaquette and associates found that administrators at the four universities cited the need to increase revenue and minimize costs as a result of declining state funding. Additionally, the authors found a positive relationship between RCM and tuition revenue at Iowa State University (ISU), Kent State University (KSU), and the University of Cincinnati (UC) but did not find an increase at the University of Florida (UF). Deering and Sá (2014) investigated institutions' motivations for adopting RCM at three public Canadian universities: the University of Toronto (UT), the University of Lethbridge (UL), and Queen's University (QU). Overall, the authors found that the adoption of RCM was a strategic decision in response to declining government funding and years of financial constraints experienced by the institutions in the study (Deering & Sá, 2014).

With regard to institutions' mixed experiences with RCM, Lang (2002) examined RCM at the University of Toronto (UT). The researcher revealed that UT developed several self-funded programs after RCM was implemented, including an executive masters of business administration program, a doctor of pharmacy program, and an elementary school. However, Lang (2002) noted that one of UT's campuses had accumulated a \$5.5 million debt after RCM was implemented. Hearn, Lewis, Kallsen, Holdsworth, and Jones (2006) explored the impact of RCM at the University of

Minnesota-Twin Cities (UMTC) and found mixed results. Hearn and associates found that some colleges and schools within UMTC experienced increases in enrollment, and the number of credit hours taught; however, some colleges and schools did not realize the same benefits after RCM was implemented (Hearn et al., 2006).

Additionally, due to the dearth of RCM scholarship, other findings regarding RCM have been institution-specific and unconnected to any systematic investigation. These findings include (a) perceptions of RCM budgeting as a structural process (Cekic, 2010); (b) RCM's impact on faculty workload (McBride, Neiman, & Johnson, 2000); and (c) RCM's effect on graduation rates (Rutherford & Rabovsky, 2017).

Cekic (2010) investigated RCM at Indiana University-Bloomington (IUB) to identify how faculty and administrators' decision-making processes for budgeting changed after the implementation of RCM. The researcher used Bolman and Deal's (2003) four organizational frames (i.e., structural frame, human resource frame, political frame, and symbolic frame). He found that interviewees aligned more closely with the structural frame, suggesting that RCM was more bureaucratic and policy-driven than driven by political and competitive considerations.

McBride et al. (2000) investigated RCM at an academic-unit level (i.e., within a college/school), specifically to examine RCM in relation to faculty time and effort at Indiana University-Purdue University Indianapolis' (IUPUI) School of Nursing. They found that faculty allocated their time differently after RCM had been implemented (McBride et al., 2000). Finally, using panel data, Rutherford and Rabovsky (2017) examined the relationship between utilizing RCM on two outcomes: graduation rates and degree production at four-year public and private institutions. They found a positive



significant relationship between graduation rates and the use of RCM but did not find a significant relationship for degree production (Rutherford & Rabovsky, 2017).

Despite inroads made by the aforementioned research studies, an examination of how, if at all, the utilization of RCM impacted costs at public research universities was still absent from the empirical literature. The results of this study provide insight into this inquiry.

### **Summary of the Literature on Higher Education Costs**

Unlike the paucity of empirical literature on RCM, the body of scholarship on higher education costs is vast and voluminous (Agasisti & Salerno, 2007; Brinkman & Leslie, 1986; Cohn, Rhine, & Santos, 1989; deGroot, McMahon, Volkwein, 1991; Doyle, 2015; Johnes & Schwarzenberger, 2011; Koshal & Koshal, 1999; Laband & Lentz, 2003; Nelson & Hevert, 1992; Robst, 2001; Sav, 2004; Titus et al., 2017; Toutkoushian, 1999). Researchers have extensively theorized and empirically assessed the nature of costs in higher education (Baumol & Bowen, 1966; Bowen, 1980). Within these domains, scholars have provided insight into three broad lines of inquiry: (1) to explain why higher education costs rise faster than costs in other industries; (2) to identify opportunities for efficiencies within and across colleges and universities; and (3) to understand the relationship between revenues and costs among higher education institutions.

The literature has revealed four major theories that undergird research into why higher education costs rise faster relative to costs in other industries: Cost Disease Theory (Baumol & Bowen, 1966), Revenue Theory of Costs (RTC) (Bowen, 1980), the Positional Arms Race Theory, and Principal-Agent Theory (PAT). Although each of these theories provides insight into cost increases in higher education, debates remain

ongoing regarding which one of these theories most closely describes why higher education costs continue to rise.

In addition to the theoretical perspectives used to explain why higher education costs rise, the empirical literature has identified factors that contribute to cost increases in colleges and universities. Those factors include institutions' size, scope, level of instruction, academic program mix, revenues, and geographical/regional locations. Specifically, empirical studies have explored these determinants of costs and have elucidated opportunities for efficiencies in higher education by (a) identifying economies of scale, which are present if an increase in any output such as enrollment would result in a decrease in costs; (b) identifying economies of scope, which are present if producing two or more products (e.g. undergraduate and graduate education) jointly would decrease costs; and (c) assessing the extent to which colleges and universities are cost efficient, which estimates the minimum cost for producing a given level of outputs (Agasisti & Salerno, 2007; Brinkman, 1981; Brinkman & Leslie, 1986; Cohn et al., 1989; deGroot et al., 1991; Doyle, 2015; Johnes & Schwarzenberger, 2011; Koshal & Koshal, 1999; Koshal et al., 2001; Kuo & Ho, 2007; Laband & Lentz, 2003, 2004; Mamun, 2012; Nelson & Hevert, 1992; Robst, 2001; Sav, 2004; Titus, et al., 2017; Toutkoushian, 1999).

Researchers (Cohn et al., 1989; deGroot et al., 1991; Koshal & Koshal, 1999; Koshal et al., 2001; Laband & Lentz, 2003; Nelson & Hevert, 1992; Sav, 2004; Titus et al., 2017; Toutkoushian, 1999) have generally found positive returns to scale, which suggests that colleges and universities could lower unit costs by increasing enrollment, for example. Additionally, researchers have also generally found positive returns to scope – that is, whether there are lower costs per unit when institutions increase the production

of multiple outputs simultaneously, such as research and undergraduate education (Cohn et al., 1989; Koshal & Koshal, 1999; Koshal et al., 2001; Laband & Lentz, 2003; Sav, 2004; Toutkoushian, 1999).

Scholars have also shown that costs vary by academic discipline (Agasisti & Salerno, 2007; Brinkman, 2000; deGroot et al., 1991; Johnes & Schwarzenberger, 2011; Kuo & Ho, 2007; Mamun, 2012; Sav, 2004), level of instruction (Brinkman, 1981; deGroot et al., 1991; Koshal & Koshal, 1999; Koshal et al., 2001; Laband & Lentz, 2003; Nelson & Hevert, 1992), revenue allocations (Leslie et al., 2012; Robst, 2001), and geographical location (Sav, 2004; Titus et al., 2017; Toutkoushian, 1999).

Although scholars have provided significant insight into higher education costs, they have not explored how specific colleges and universities have responded to cost escalation via new policies or practices, such as RCM. Specifically, the extant literature examines costs broadly across hundreds of colleges and universities, such that few studies have explored institution-specific costs using smaller sample sizes. Small-sample studies may enable researchers to provide additional context around institutional practices such as RCM to show how specific colleges and universities have responded to rising costs. Only one study (Nelson & Hevert, 1992) investigated cost at a single institution (i.e., the University of Delaware). However, the scholars (Nelson & Hevert, 1992) did not provide significant context around the institution's financial circumstances. Additionally, the scholars did not indicate how the university responded – for example, by implementing new policies – to address cost escalation. Several scholars (Cheslock, Ortagus, Umbricht, & Wymore, 2016; Titus et al., 2017; Toutkoushian, 1999) have noted that an investigation into decentralized budget models, such as RCM, is warranted given

RCM's perceived implications on higher education costs. This study addressed this gap in the literature, specifically by examining RCM's impact on total operating costs at two public research universities.

### **Statement of the Problem**

Several national organizations and associations have encouraged more research on effective ways for universities to manage their financial resources. For example, the Lumina Foundation commissioned a series of papers that examined ways that colleges and universities could leverage and align their internal finances to incentivize and promote student success. Among the papers commissioned by the Lumina Foundation, Kosten (2016) explored the ways in which RCM could be used by colleges and universities to achieve the shared goals of their states, the institutions, and their students.

Additionally, Askin and Shea (2016) of the National Association of College and University Business Officers (NACUBO) provided a comprehensive review of the financial constraints faced by many institutions. Askin and Shea (2016) called on the higher education community to consider new methods to manage their financial resources. Specifically, they noted: "If colleges and universities are to thrive, change must be proactive and strategic and match the pace of the rapidly evolving world around them" (Askin & Shea, 2016, p. 17). They indicated that some universities have considered RCM as a means to adapt to the changing financial picture (Askin & Shea, 2016). However, an empirical investigation regarding whether RCM could positively impact an institution's finances had not yet been conducted.

Given the financial landscape of public higher education regarding declining state support, escalating costs, rising tuition prices, as well as the recent attention and adoption of RCM as a strategy to minimize costs (among other goals), more empirical evidence is warranted. Therefore, in order to provide public policymakers and college and university administrators with insight regarding RCM's effect on costs, research on the topic must be developed.

### **Purpose of the Study**

The purpose of this study is to examine the effect of RCM on total operating costs at two public research universities in the United States. Specifically, this study is designed to uncover if, and to what extent, RCM as a budget model and management tool impacted operating costs at the University of New Hampshire and the University of Arizona. This study is guided by the following research question:

- *What is the impact of RCM on total operating costs at two public research universities in the United States?*

### **Summary of the Research Design**

#### **Summary of the Methodological Approach**

This study utilizes a method called the synthetic control methodology (SCM) to address the research question. Specifically, SCM is a quantitative, data-driven method developed in economics (Abadie & Gardeazabal, 2003; Abadie, Diamond, & Hainmueller, 2010, 2015) to estimate the causal effects of policies, programs, idiosyncratic events, or interventions. SCM was introduced into research by Abadie and

Gardeazabal (2003) to assess the effect of terrorism on economic growth in Basque Country. Since 2003, SCM has been used in several other economic studies (e.g., Abadie, Diamond, & Hainmueller, 2010, 2015; Adhikari, Duval, Hu, & Loungani, 2018; Barone & Moceti, 2014; Becker & Klobner, 2016; Biagi, Brandano, & Pulina, 2016) to investigate the economic impact of various policies. Additionally, SCM has been employed in public health (Krief, Grieve, Hangartner, Turner, Nikolova, & Sutton, 2016), criminal justice (Rydberg, McGarrell, Noris, & Circo, 2018), and higher education (Bonander, Jakobsson, Podesta, & Svensson, 2016; Hinrichs, 2012; Liu, 2015; Jaquette et al., 2018). A robust discussion and description of the methodology are contained in *Chapter 3: Methodology*. However, a brief summary of SCM is provided below.

Generally, SCM aims to approximate the treatment effect of a given policy, program, or event using a data-driven statistical process. Specifically, the statistical process is first used to construct a control group (i.e., the group that did not experience or receive the policy, program, or intervention – known as the *synthetic control unit*). Next, the SCM statistical process estimates the treatment effects, if any, by comparing the post-treatment outcome of the synthetic control unit to the post-treatment outcome of the treated unit (i.e., the unit that experienced the policy, program, or intervention). The purpose of the synthetic control unit varies between the pretreatment period of the study (i.e., the period before the treatment occurred) and the post-treatment period of the study (i.e., the period after the treatment occurred). Specifically, in the pretreatment period, the synthetic control unit is used primarily to resemble the treated unit (i.e., possess nearly the same characteristics). In the post-treatment period of the study, the purpose of the synthetic control unit is to estimate the post-treatment *counterfactual*. The counterfactual

is defined as the post-treatment outcome of the treated unit in the absence of the treatment (Krief et al., 2016). The counterfactual is used to assess treatment effects (if any) by subtracting the post-treatment outcome (i.e., the outcome variable) of the treated unit from the post-treatment outcome of the counterfactual. If there is a difference between the outcome of the treated unit and the estimated outcome of the synthetic control unit (i.e., the post-treatment counterfactual), then there is a treatment effect. However, if there is no difference between the outcome of the treated unit and the estimated outcome of the synthetic control unit, then there is no treatment effect. An illustrative example from a prior study on RCM using SCM is described next to put SCM in context.

Jaquette et al. (2018) utilized SCM to examine the impact (i.e., treatment effect) of RCM on tuition revenue at four public research universities: Kent State University, University of Florida, Iowa State University, and the University of Cincinnati. Specifically, Jaquette et al. (2018) estimated a synthetic control unit (i.e., control group) and counterfactual for each of the four universities in the study. For example, using the SCM statistical procedure (discussed further in *Chapter 3: Methodology*), the authors generated a synthetic control unit for Kent State University (hereafter called *synthetic Kent State*) by first identifying a pool of similar universities that had not implemented RCM and then by choosing which of those non-treated universities best resembled Kent State University in the pretreatment period of the study (i.e., prior to Kent State's implementation of RCM in the academic year 2008-09). Synthetic Kent State was composed of five universities that had not implemented RCM: Ohio University, Western Michigan University, University of North Texas, Miami University-Oxford, and Purdue

University-Main Campus. After Jaquette et al. (2018) estimated synthetic Kent State, they approximated the post-treatment counterfactual on tuition revenue (i.e., the estimation of what would have occurred at Kent State University in the absence of implementing RCM) to determine the treatment effects. The authors revealed that tuition revenue had significantly increased each year after RCM had been implemented at Kent State. The process for assessing the treatment effects was done by comparing the tuition revenue of Kent State to the estimated tuition revenue of synthetic Kent State. This procedure was conducted for the remaining three universities in Jaquette et al.'s (2018) study.

SCM was employed in this study in a similar manner as it was used by Jaquette and associates (2018). However, this study focused on total operating costs at two public research universities. SCM was deemed the most appropriate method because it allows researchers to estimate a post-treatment counterfactual in small-sample studies when other quasi-experimental methods fall short (Abadie et al., 2003; Abadie et al., 2010, 2015; Jaquette et al., 2018). Researchers have used other techniques to estimate policy effects, including the difference-in-differences (DID) approach, ordinary least squares regression, propensity score matching, and instrumental variables regression. The limitations of these methods will be discussed in *Chapter 3: Methodology*. However, generally, these methods are inappropriate for a study on RCM for several reasons. For example, each of these methods estimates an *average* treatment effect across several units. In contrast, the SCM can estimate actual treatment effects across one unit at a time. This is beneficial for small-sample studies that examine policies, programs, and interventions that may not be widespread across multiple units (e.g., institutions,



organizations, states, etc.). Additionally, DID (and the other methods listed above) are limited (among other reasons noted in *Chapter 3: Methodology*) because they do not provide the researcher with an indication of the extent to which the estimated control group resembles the treated unit (in the pretreatment period). The SCM, however, provides the researcher with information on the extent to which the estimated control group (i.e., the synthetic control unit) resembles the treated unit. Additionally, SCM provides the researcher with data on how well each of the variables in the study help to predict the outcome variable under investigation. These features of SCM are important from a methodological perspective because they provide greater clarity and confidence when assessing treatment effects. (A more robust discussion on the appropriateness of SCM is discussed in *Chapter 3: Methodology*.)

### **Summary Descriptions of the Institutions in the Study**

This study examines the effect of RCM on total operating costs at two public research universities: the University of New Hampshire (UNH) and the University of Arizona (UofA). These public research universities were selected for several reasons: First, as will be described below, leaders of each of these institutions cited (among others) that their motivation to implement RCM was to incentivize cost minimization across their respective institutions. Because universities that use RCM have cited different reasons for implementing it, the intent of university leaders at UNH and UofA to implement RCM as a means to minimize costs was a key factor in selecting them for this study. Secondly, these institutions were selected because there was adequate public data available with regard to how UNH and UofA operate their RCM models. Additionally, there was sufficient public record available on each of the institutions'

websites (e.g., downloadable reports, manuals, and personal communications) to understand the context in which these universities operated when they implemented RCM. An adequate public record was not available on the websites or in the records of other universities that were considered for this study. Third, as illustrated in Table A2, each of these institutions has different levels of experience with RCM – specifically, UNH adopted RCM in the year 2000 and UofA adopted RCM in 2015. Fourth, UNH and UofA implement RCM differently – that is, they employ different funding formulas and allocation rules. An investigation of RCM at two very different universities was important because it would create more knowledge of how RCM manifests itself across multiple campuses. Finally, the synthetic control method (the method used in this study) allows the researcher to assess the treatment effects of one unit (i.e., university) at a time. Therefore, the number of cases that are selected by the researcher is inconsequential (i.e., there is no minimum or maximum number required).

### **University of New Hampshire**

The University of New Hampshire (UNH) is a public research university located in Durham, New Hampshire. UNH is the state flagship institution – enrolling over 13,000 undergraduates and over 2,000 graduate students across 13 colleges and schools in 2018 (UNH Facts and Figures, 2019). Additionally, UNH manages a nearly \$600 million operating budget and offers associate’s degrees, baccalaureate degrees, and graduate degrees across 200 academic programs (UNH Facts and Figures, 2019).

With regard to RCM, after an 18-month exploration study was conducted by the RCM Steering Committee, President Joan Leitzel furnished a memo on January 14, 2000, to the campus community announcing her decision to implement RCM by July 1, 2000.

President Leitzel cited five reasons for deciding to move the campus to RCM. Among them, she noted, “[t]here will be stronger incentives for cost effectiveness and revenue generation” (Joan Leitzel, personal communication, January 14, 2000). Indeed, between 1980 and 1999 (the year prior to RCM implementation), total operating costs increased by 71% (after adjusting for inflation in 1999 dollars). Thus, the leaders of UNH sought, in part, to control costs as the institution became more reliant on tuition revenue versus public funding from the state.

Since year one of RCM implementation (i.e., the year 2000), the UNH’s RCM model and funding formulas have been reviewed and modified at least three times: in 2006, 2009, and 2015. This study focuses on UNH’s original funding formula to analyze RCM’s effect on total operating costs (see Table A2). (Further discussion regarding the decision to focus on UNH’s original RCM model is contained in *Chapter 3: Methodology*). On the revenue side, the UNH’s original RCM funding formula allocated the majority of undergraduate tuition revenue to the academic units (83%). Fifteen percent of undergraduate tuition revenue was allocated to the Division of Continuing Education and two percent was distributed to the library. Graduate tuition revenue was similarly allocated with 98% going to the academic unit and two percent to the library. Finally, revenue from state appropriations were used to fully fund the support units first and the remaining funds were distributed to the library (20%), to the academic and research units (30%), and the remaining funds were used to support the “hold harmless” fund.

As it relates to costs, academic units at UNH were responsible for their own (direct) expenses (e.g., faculty/staff salaries, fringe benefits, equipment, travel, etc.) under

the original RCM formula. The indirect expenses incurred by the academic units were paid using two assessments: an academic affairs assessment “tax” and a general assessment “tax” to central administration. These assessments were based on 50% of personnel expenses and 50% of overall revenue. Lastly, the direct and indirect expenses of the support centers were paid for using revenue from state appropriations, as noted previously.

### **University of Arizona**

The University of Arizona (UofA) is a public research university established in 1885 and serves as the state of Arizona’s flagship university. In 2018, UofA enrolled over 45,000 undergraduate and graduate students across 40 colleges and schools, including two hospitals (University of Arizona, 2019). Moreover, in 2018, the campus managed a nearly \$2.4 billion operating budget (University of Arizona, 2019).

The changing financial picture at UofA prompted administrators to consider RCM. Specifically, between 2003 and 2014 (the year before RCM was implemented), UofA experienced a 34% decline in state appropriations (after adjusting for inflation in 2014 dollars). Despite the decline in state appropriations, undergraduate enrollment increased by 16% and graduate enrollment rose by eight percent between 2003 and 2014. Moreover, total expenses rose by nearly 30% between 2003 and 2014 – pacing at nearly the same rate as revenue growth during this period. In the fall of 2012, the UofA provost convened a steering committee to investigate the feasibility of implementing RCM. Between fall 2012 and fall 2013, the steering committee met to develop the guiding principles for RCM and identify key personnel and campus units to ensure RCM’s success. By the spring of 2014, the UofA began testing components of RCM on a small

scale. In the fall of 2014, UofA operated concurrent budgets – one using the old system and the other using a prototype of RCM. After testing had been completed, the steering committee formally recommended to the president of UofA that RCM be fully implemented beginning July 1, 2015.

The UofA's RCM funding formulas regarding revenue are standard.

Undergraduate tuition revenue is pooled and then allocated based on credit hours taught (i.e., 75% of all undergraduate tuition revenue is allocated to the academic units based on how many credit hours are taught). The remaining 25% of undergraduate tuition revenue is allocated to the academic units based on the number of students enrolled in academic majors housed by those units. Graduate tuition revenue follows the student – specifically, it is allocated based on credit hours (i.e., 75% of a graduate student's tuition dollars are allocated to the academic units that provide instruction to that student) and major (i.e., the remaining 25% of a graduate student's tuition dollars are allocated to the academic unit that houses the student's major). Lastly regarding revenues, state appropriations are the primary source of the subvention pool and is used to cover the expenses of responsibility centers that may experience a shortfall.

On the cost side, responsibility centers at the UofA are also fully responsible for their expenses. Nearly 31% of undergraduate tuition revenue is used to pay the costs of support centers, 12.38% of graduate tuition is used to pay for support center expenses, and 2.75% is taken from both graduate and undergraduate tuition to pay for the Strategic Initiative Fund and facilities fees.

## **Summary of the Theoretical Frameworks**

This study is guided by two theoretical frameworks: Principal-Agent Theory (PAT) and Bowen's (1980) Revenue Theory of Cost (RTC). PAT has been used by economists, political scientists, and higher education researchers to explain the contractual relationship between two or more entities (Cheslock et al., 2016; Jaquette et al., 2018; Lane & Kivisto, 2008; Martin, 2011; Tandberg et al., 2017; Titus, 2009). Specifically, PAT posits that a principal contracts the services of one or multiple agents to perform duties in which the principal does not have the time, knowledge, skill, or desire to perform him/her/itself (Lane & Kivisto, 2008). PAT is used to provide a conceptual framework on the principal-agent relationship between central administration (i.e., the principal) and deans (i.e., the agents) at two public research universities that adopted RCM – consistent with previous research by Jaquette et al. (2018). This dissertation study, unlike Jaquette et al. (2018), used PAT to explain the principal-agent relationship between central administration and deans with regard to RCM's impact on costs.

RTC posits that colleges and universities function with the goal of maximizing their prestige, excellence, and influence (Bowen, 1980). To carry out their goals with regard to prestige maximization, RTC suggests that institutions of higher education raise as much money as they can, and then spend all of the money they raise (Bowen, 1980). Moreover, because there is no discernable way to identify when an institution has maximized its prestige, excellence, or influence, Bowen (1980) further posits that spending is incessant. This further suggests two notions: (a) colleges and universities are

not cost minimizers; and (b) cost escalation in higher education is the result of institutional choice

RTC is utilized in this study to theoretically frame the impact of revenues on costs as shown by previous research (Leslie, Slaughter, Taylor, & Zhang, 2012). Specifically, this study incorporated variables on college and university revenue sources because RTC suggests that there is a positive relationship between revenues and costs.

PAT and RTC were selected for at least two reasons. First, previous research on RCM by Jaquette et al. (2018) has shown that PAT is an effective perspective to explain the relationship between central administration and responsibility center leaders (i.e., deans). Secondly, previous research on RTC (e.g., Leslie et al., 2012) illustrates that college and university revenues can impact costs (i.e., how colleges and universities spend their money). Therefore, PAT is used to theoretically frame the central administration-dean relationship and RTC provides a framework for the inclusion of revenue variables in this study.

### **Description of the Data and Variables**

The data and variables in this study are adopted from the extant literature on higher education costs which will be further described in *Chapter 3: Methodology*. To address the research question, I developed and used two institution-level panel datasets (one for each university in the study). Data were extracted from the Integrated Postsecondary Education Data System (IPEDS). As illustrated in Table A3, the outcome variable is total operating costs and is defined as the sum of expenditures on academic administration, institutional administration, instruction, and student services. Total operating costs was selected as the outcome variable for at least two reasons: (1) it

represents the finances over which university administrators possess the greatest control year-over-year (i.e., long-term expenses, such as the payment of debt, are not included because such agreements do not fluctuate annually nor do administrators possess significant control over them); and (2) RCM seeks to incentivize cost minimization among administrators. Thus, total operating costs is an appropriate variable to illustrate if, or to what extent, RCM affected the costs in which college and university administrators possessed the most control.

The predictor variables in the study have been adopted from previous research on higher education costs. Specifically, these empirical studies (Archibald & Feldman, 2018; Brinkman, 1981, 2000, 2006; Cohn, et al., 1989; deGroot et al., 1991; Doyle, 2015; Laband & Lentz, 2003; Robst, 2001; Sav, 2004; Titus et al., 2017) have revealed several determinants of costs (e.g., institutional size, institution scope, undergraduate versus graduate education costs, academic program mix, and revenues) that were used in this study. (Further discussion regarding determinants of costs in higher education is in *Chapter 2: Literature Review*.) Specifically, to represent scale (size), scope, and level of instruction, the following variables were gleaned from previous research: full-time equivalent undergraduate enrollment, graduate headcount, the number of full-time faculty, research expenditures, and the average faculty salary. To represent academic program mix, the proportion of students graduating with degrees in science, technology, engineering, and mathematics (STEM) out of the total number of graduates was included. Additionally, to theoretically frame the RTC, the following revenue variables were included: tuition and fee revenue, state appropriations, private gifts, grants, and contracts,



the proportion of tuition and fee revenue out of total revenue, and the proportion of state appropriation revenue out of total revenue.

The choice of predictor variables was motivated by two factors: (1) the existing literature on higher education cost as described in *Chapter 2: Literature Review* (Archibald & Feldman, 2018; Brinkman, 1981, 2000, 2006; Cohn, Rhine, & Santos, 1989; deGroot, McMahon, & Volkwein, 1991; Doyle, 2001; Hillman, 2012; Jaquette et al., 2018; Laband & Lentz, 2003; Robst, 2001; Sav, 2007; Titus, et al., 2017); and (2) the SCM allows the researcher to select predictors of the outcome variable (i.e., in this case, total operating costs). Specifically, variables that do not possess strong predictive power are assigned a lower weight by the SCM. This feature of SCM will be further discussed in *Chapter 3: Methodology*.

### **Sample Period**

The data and variables listed above and in Table A3 were used to generate one synthetic control unit for each institution in this study. In order to generate a synthetic control unit, Abadie et al. (2015) suggest using a long pre-treatment period for two reasons: (1) to estimate a synthetic control unit that closely resembles the treated unit during the pretreatment period; (2) to estimate a reliable counterfactual in the posttreatment period.

With regard to generating a synthetic control unit for UNH (i.e., called “Synthetic” UNH), data were analyzed across a sample period between 1989-90 and 2004-05. The pre-treatment period begins in 1989-90 (the first year of consistent and available data) and ends in 1998-1999 (i.e., the year prior to RCM implementation at UNH). The post-treatment period (i.e., each year after RCM implementation) is five

years. I selected a five-year post-treatment period for two reasons. First, it is consistent with prior research (Hearn et al., 2006; Jaquette et al., 2018). Hearn et al. (2006) and Jaquette et al. (2018) examined the impact of RCM between one and five years after it had been implemented at the institutions in their respective studies. Secondly, and perhaps more importantly, the UNH reviewed and modified its original RCM formulas and policies after the fifth year. Therefore, in order to capture the initial impact of RCM on costs, I evaluated the post-treatment effects of RCM on total operating costs in 2000-01, 2001-02, 2002-03, 2003-04, and 2004-05.

The University of Arizona implemented RCM in 2015. Thus, the RCM model is relatively new and does not have many post-treatment observations due to data availability. The overall sample period begins in 1989-90 (the first year of consistent and available data) and ends in 2017-18 (the most recent and available data in IPEDS). The pre-treatment period extends from 1989-90 and ends in 2013-14 (i.e., the year prior to RCM implementation). The treatment effects were evaluated for three years: in 2015-16, 2016-17, and 2017-18. Three years of post-treatment analysis was sufficient to generate robust results.

### **Limitations**

Although this study sheds light on RCM's effect on total operating costs at two public research universities in the United States, there are at least three limitations worth noting. First, RCM incentivizes (among other goals) cost minimization at the academic unit level (e.g., schools, colleges, and departments) through the use of funding formulas and devolved financial responsibility (Curry et al., 2013; Strauss & Curry, 2002; Whalen, 1991). However, data at this level are unavailable. Therefore, this study is limited in that

it cannot discern how RCM might have impacted costs at the individual colleges or schools within the universities in the study because data are reported in the aggregate (i.e., at the institution level). Thus, I assumed implicitly that the impact of RCM on costs is in the aggregate as well. However, the results (as will be discussed in *Chapter 4: Results*) show that this may have not been the case.

In addition to data availability, this study is limited by its definition of RCM implementation. Specifically, I refer to institutions that have fully implemented RCM under a formal review process commissioned by the president or provost of the university – several of which are listed in Table A1. However, as described above, the SCM technique requires the researcher to identify a donor pool of untreated units in order to generate a viable synthetic control unit. Because there is no central database of institutions that use RCM, it is possible that the donor pools that were used to generate a synthetic control unit for each of the universities in this study included some institutions that use RCM. To mitigate the possibility of including institutions that have adopted RCM in the donor pool, I used the list of RCM universities developed by Curry et al. (2013), adopted by Jaquette et al. (2018), and supplemented with reports and websites for universities that have adopted RCM (see Table A1).

Third, this study is limited because it only examined total operating costs at two public research universities. There are a number of other public and private universities that have not received scholarly attention (Hearn et al., 2006; Lang, 2002; Jaquette et al., 2018). Thus, there is considerable opportunity for research across more universities – public and private – to better generalize the findings on RCM’s impact. Due to this limitation, the results are not generalized beyond the institutions in the study.

## Significance of the Study

### Summary of the Results

The results of this study show that RCM positively impacted total operating costs at both the UNH and UofA. With regard to UNH, the results of the synthetic control analysis reveal that RCM positively impacted total operating costs between 2001 and 2005. However, the estimated *p-values* across the post-treatment period were not low enough to infer causality (*p-value*  $\leq 0.10$ ). Additionally, with regard to the UofA, the results causally infer that RCM increased total operating costs after the first year of implementation. Specifically, total operating costs were \$108.51 million higher than they would have been if RCM had not been implemented (*p-value*  $\leq 0.10$ ). Additionally, the results show that RCM positively impacted costs in the second and third years after RCM had been implemented but the *p-values* did not conclude that RCM had a causal effect on total operating costs in those years (*p-value*  $\leq 0.10$ ).

### Summary of the Contributions to Research

Despite the limitations described above, this study contributes to research in several ways worth noting. First, this study is the first to bridge the gap between the RCM literature and the higher education cost literature by providing empirical insight regarding RCM's effect on total operating costs. Second, this study contributes to the use of theory in the RCM literature because it incorporates two theoretical frameworks to guide the research question: the principal-agent theory (PAT) and Bowen's (1980) revenue theory of cost (RTC). Only two previous studies (Cekic, 2010; Jaquette et al., 2018) from the RCM literature were theoretically grounded. Third, this study contributes to the literature because it overcame several methodological limitations of previous research (Lang, 2002;

Hearn et al., 2006; Rutherford & Rabovsky, 2017) by employing SCM to assess causal effects of RCM's impact. Specifically, the use of SCM in this study did not rely on qualitative methods to describe the quantitative effects of RCM (this notion is further described in *Chapter 2: Literature Review*). Additionally, the use of SCM in this study went beyond descriptive statistics (Hearn et al., 2006) and regression analysis (Rutherford & Rabovsky, 2017) which inferred correlation rather than causality to draw conclusions.

### **Summary of the Contributions to Practice**

In addition to research contributions, this study contributes to practice. Prior to this study, no such research existed regarding RCM's impact on costs, and several pro-RCM publications (Curry et al., 2013; Hanover Research, 2008; Strauss & Curry, 2002; Whalen, 1991) relied heavily on descriptive statistics and anecdotal evidence to make claims about RCM's utility. The results of this study – specifically that RCM positively impacted total operating costs – balance previous anecdotal claims by providing empirical insight on RCM at UNH and UofA to guide future decision-making. More broadly, this study provides insight regarding RCM's effect on total operating costs using two examples (i.e., UNH and UofA) to public policymakers and university administrators that may be considering RCM. This is especially important given substantial declines in state funding per FTE and calls for greater accountability and efficiency described above.

## Chapter 2: Literature Review

### Introduction

The purpose of this study is to examine the effects of Responsibility Center Management (RCM) on total operating costs at two public research universities in the United States. Specifically, this study was designed to uncover if RCM as a budget model and management approach helped college administrators at two public research universities achieve one of RCM's core goals of minimizing costs. This study is guided by the following research question: *What is the impact of RCM on costs at two public research universities in the United States?*

To address the research question, this study draws from two literature domains: literature on RCM and literature on costs in higher education and uses two theoretical frameworks: principal-agent theory and Bowen's (1980) revenue theory of cost. Additionally, this study employs a quantitative technique known as the synthetic control methodology (SCM) to address the research question and provide causal inference. This chapter discusses and critiques the extant literature on RCM and higher education costs and describes how the theoretical frameworks are used to address the research question. This chapter is divided into four major sections: (1) Scholarship on RCM; (2) Scholarship on Higher Education Cost; (3) Gaps and Limitations in Prior Research; and (4) Addressing the Gaps and Limitations in Prior Research.

## **Scholarship on RCM**

### **Empirical Literature on RCM**

The scholarly literature on RCM is scant and unconnected to any systematic investigation. Specifically, scholars have not yet developed a comprehensive research agenda to examine RCM's impact. As a consequence, only two broad findings exist: (1) colleges and universities have primarily implemented RCM to enhance their financial positions (i.e., to generate additional revenue and minimize costs); and (2) institutions have realized mixed experiences (i.e., positive and negative) with RCM. Additionally, due to the dearth of RCM scholarship, other findings regarding RCM have been institution-specific and unconnected to any systematic investigation of its impact. These findings include perceptions of RCM budgeting as a structural process (Cekic, 2010); RCM's impact on faculty workload (McBride et al., 2000); and RCM's impact on graduation rates (Rutherford & Rabovsky, 2017). The various research findings regarding RCM's impact will be discussed below.

### **Motivations for Adopting RCM: Generate Revenue and Minimize Costs**

At least two empirical studies (i.e., Deering & Sá, 2014; Jaquette et al., 2018) and several non-empirical publications (Curry et al., 2013; Strauss & Curry, 2002; Whalen, 1991) have indicated that RCM has been adopted primarily as a means to increase revenues and decrease (or control) costs. Among public research universities specifically, RCM has been adopted in reaction to declining state appropriations to higher education (Deering & Sá, 2014; Jaquette et al., 2018; Lang, 2002). For example, in a recent empirical study, Jaquette et al. (2018) examined the effect of RCM on tuition revenue at four public research universities: Kent State University (KSU), Iowa State University

(ISU), University of Florida (UF), and University of Cincinnati (UC). The scholars sought to address at least two research objectives: first, to identify why the administrators at each of these institutions intended to implement RCM; and second, to reveal the extent to which RCM impacted tuition revenue (Jaquette et al., 2018).

Using publicly available documents, reports, and website content, the scholars found that RCM was adopted for similar reasons at each of the institutions in the study. Specifically, administrators at these universities cited the need to increase revenue and minimize costs as a result of declining state funding. ISU adopted RCM in 2008-09 after several years of declining state appropriations, decreased enrollment, and lower tuition revenue. The university president at ISU stated that the aim of RCM was to incentivize revenue generation and cost reduction (Jaquette et al., 2018). KSU adopted RCM in 2008-09 also as a result of state budget cuts, declining enrollment (Jaquette et al., 2018). Among other goals, such as to improve decision making, the president of UC noted that a primary goal for implementing RCM was to generate revenue as a consequence of state and federal funding decreases. UC adopted RCM in 2009-10. Lastly, the president at UF indicated that UF needed to become more self-sustaining since the state had experienced several years of declining funding. UF fully adopted RCM by 2010-11.

Further analysis was conducted by Jaquette et al. (2018) to uncover the extent to which RCM impacted tuition revenue at each of the four institutions. The scholars utilized the synthetic control methodology (SCM) to conduct this analysis. The SCM has been used in small-sample case studies to quantitatively assess the effect, if any, of an event, policy, or treatment. (This method will be described briefly below and in greater detail in *Chapter 3: Methodology*.)



Using the SCM procedure, Jaquette et al. (2018) constructed a panel dataset using data extracted from the Integrated Postsecondary Education Data System (IPEDS). Tuition revenue was the outcome variable. The independent variables included data on known research variables that affect tuition revenue, including undergraduate full-time enrollment, graduate headcount, undergraduate resident tuition price, and revenue from various sources (e.g., state appropriations, state grants, and contracts revenue, private grants and contracts, and auxiliary enterprises). Additionally, the researchers included cost variables (i.e., instructional expenditures, research expenditures, academic affairs and student support, institutional support, and auxiliary expenditures). Lastly, Jaquette and associates included variables to account for institution selectivity (e.g., 2004 Barron's selectivity and institutional discount rate), and nonresident tuition revenue using undergraduate nonresident tuition price and the percent of nonresident freshmen.

Jaquette et al. (2018) found a positive relationship between RCM and tuition revenue at ISU, KSU, and UC. The scholars showed that by 2013-14, RCM had increased tuition revenue by nearly \$44 million at ISU. Similarly, the researchers found that KSU had increased tuition revenue by \$34 million - three years after implementing RCM. UC increased tuition revenue by \$45 million by 2013-14. However, the authors did not find that RCM had significantly impacted tuition revenue at UF.

Jaquette et al. 's (2018) study not only documented institutions' motivations for adopting RCM but also became the first study to evidence that RCM can have a positive impact on tuition revenue. Previous studies (as will be described below) have either failed to use appropriate methods, such as SCM or have not causally analyzed RCM's effect on other financial outcomes. The results associated with this study, while not generalizable,

have provided significant insight into RCM across multiple cases – specifically, the four universities in the study. Additional merits regarding this study will be discussed below.

Deering and Sá (2014) investigated institutions' motivations for adopting RCM at three public, Canadian universities: the University of Toronto (UT), the University of Lethbridge (UL), and Queen's University (QU). The scholars analyzed institutional documents and interviewed 31 senior university leaders and faculty. Overall, the authors revealed that the adoption of RCM was a strategic decision at these universities. Specifically, several interviewees indicated that RCM was adopted in response to years of financial constraints experienced by the institutions in the study (Deering & Sá, 2014).

For example, QU – which enrolled over 20,000 students and oversaw an operating budget greater than \$400 million – experienced enrollment growth between 2001 and 2011. Specifically, enrollment grew by 32% during that period (Deering & Sá, 2014). As a result, QU's student aid expenditures had grown by 40% between 2001 and 2011. However, government support to QU had only grown by eight percent. Thus, the administrators at QU noted that they implemented RCM in 2013 in an effort to incentivize cost containment and revenue growth since government support continued to decline (Deering & Sá, 2014).

Similarly, a senior administrator at UT – which operated three campuses and enrolled over 80,000 undergraduate and graduate students in 2006 – indicated that RCM was necessary to incentivize discipline with regard to financial responsibility. This was also due to declining government resources (Deering & Sá, 2014).

Lastly, UL maintained a \$162 million budget, managed three campuses, and enrolled approximately 8,200 graduate and undergraduate students by 2012-13. UL

adopted RCM in 1994 after the provincial government of Alberta cut university budgets. A senior leader at UL discussed that RCM was adopted to generate revenue and to increase efficiency. One academic dean indicated the future of UL would have been doubtful if RCM had not been implemented (Deering & Sá, 2014).

Despite evidence showing that these Canadian universities selected RCM in response to financial funding pressures, Deering and Sá (2014) did not investigate if RCM made a difference in revenue growth or cost containment. Several senior university leaders and deans believed that RCM helped to improve each of their institutions' financial footing. However, the study would have been strengthened if the authors analyzed whether RCM had positively impacted each institutions' finances.

### **Mixed Experiences with RCM**

Although some senior university leaders have sought and successfully implemented RCM to improve their institutions' financial positions (Deering & Sá, 2014; Jaquette et al., 2018), some universities have realized mixed experiences with RCM.

For example, in an earlier study on RCM at the University of Toronto (UT), Lang (2002) provided a comprehensive historical account of UT's experience with RCM. By the late 1990s, UT operated three campuses, enrolled nearly 52,000 students, and employed 3,100 faculty and 3,600 staff members. In his analysis of university documents, reports, and internal reviews, Lang concluded that UT's experience with RCM was mixed.

On one hand, the university experienced several successes with regard to RCM. For example, by the year 2000, UT had implemented RCM to operate many self-funded programs (Lang, 2002). These programs included: an executive masters of business

administration program, a doctor of pharmacy program, a social work diploma program, and two graduate-level accounting and financial mathematics programs (Lang, 2002). Lang (2002) also noted that UT also was able to operate an elementary and high school after RCM was implemented.

On the other hand, despite these successes, there were examples where RCM was unsuccessful at UT. For example, Lang (2002) indicated that UT had deployed RCM to UT-Scarborough (UTS) – one of UT’s three campuses. UT administrators sought for UTS to operate independently – that is, to be self-sustaining similar to the master’s programs mentioned above. UTS began the process of transitioning to RCM in 1993 and fully adopted RCM by 1997. As noted by Lang, “success would be measured in UT-Scarborough’s ability to continue to break even and to generate net revenue, either by reducing costs or by increasing income” (Lang, 2002, p. 124). In an effort to generate more revenue, Lang found that UTS had expanded enrollment in several of its programs. Based on the RCM funding formulas, UTS received more tuition revenue as enrollment increased. However, by the end of the 1999-2000 fiscal year – two years after RCM had been fully implemented – UTS had accumulated a \$5.5 million debt (Lang, 2002).

Lang (2002) offered at least two reasons why UTS experienced the \$5.5 million debt after RCM had been implemented. First, UTS’s budget projections were solely based on increases in enrollment – specifically, UTS administrators assumed that the increases in enrollment in certain programs would be coupled with additional tuition revenue and government revenue. However, the campus received a smaller share of government appropriations in the fiscal years following RCM adoption, although the scholar did not quantify the decrease in government support. He surmised that UTS’s

budget forecast for additional government revenue was too generous. However, it is difficult to discern the variance between what UTS had budgeted with regard to revenue and what was actually received since these data points are not provided.

Secondly, Lang (2002) speculated that UTS administrators, in pursuit of more revenue via increases in enrollment, may have underestimated the costs (direct and indirect) associated with expanding their programs. Specifically, the author suggested that the accumulation of debt at UTS was a consequence of not accounting for cost increases related to program expansion. He concluded the study with several implications for policy and practice. Chiefly among them, he noted the need for administrators to understand the cost implications of enrollment increases (Lang, 2002).

Despite revealing both positive and negative aspects of RCM at UT and UTS, Lang's (2002) study is limited in at least one critical way worth noting. Specifically, Lang (2002) noted that UTS had accumulated a \$5.5 million debt two years after RCM had been fully implemented. However, Lang did not conduct a quantitative or causal analysis to show that the \$5.5 million debt was a result of implementing RCM. This casts doubt on whether, and to what extent, RCM negatively impacted UTS. The study would have been strengthened if the author used an appropriate method to support that finding.

Hearn, Lewis, Kallsen, Holdsworth, and Jones (2006) explored the impact of RCM at the University of Minnesota-Twin Cities (UMTC), a large public research university that implemented RCM in 1997. This study incorporated qualitative and quantitative data and analysis to address at least three research objectives. First, Hearn et al. (2006) sought to elucidate the extent to which college-level enrollment changed post-RCM implementation. Second, the authors explored the extent to which the number of

credit hours taught by each college changed after RCM was implemented. Third, the researchers investigated how academic deans viewed RCM after it was implemented.

With regard to the first two research objectives, Hearn et al. (2006) analyzed the percentage changes in college-level enrollment and credit hours taught between 1997-98 and 2000-01. The scholars concluded that RCM impacted academic units differently and revealed several results worth noting. First, regarding college-level enrollment, the researchers showed that some colleges within UMTC realized increases in enrollment after RCM was implemented (e.g., the College of Agriculture, College of Public Affairs, and the College of Education); however, some other academic units did not increase enrollment after RCM was implemented. Thus, Hearn et al. (2006) noted that RCM created “winners” and “losers.”

Second, consistent with enrollment increases, some colleges experienced increases in the number of credit hours taught while other colleges experienced declines in credit hours taught (Hearn et al., 2006). For example, the number of credit hours taught by the College of Agriculture increased by nearly 98% between 1997-98 and 2000-01 while the number of credit hours taught by the medical school decreased by approximately 18% during the same period of time (Hearn et al., 2006).

Third, Hearn et al., (2006) estimated the average bivariate correlation of enrollment and operating revenue between 1993-94 and 1996-97 (i.e., pre-RCM implementation) and compared it to the average bivariate correlation of enrollment and operating revenue between 1997-98 and 1999-2000 (i.e., post-RCM implementation). The researchers found that the average bivariate correlation had increased from 0.92 (before RCM implementation) to 0.95 (after RCM implementation) (Hearn et al., 2006).

While this finding suggests that there is a very high correlation between enrollment and revenue, it does not conclusively signify that RCM *caused* revenue or enrollment to increase. The scholars appropriately addressed this concern by cautioning readers regarding its interpretation.

Lastly, with regard to the third research objective, Hearn et al. (2006) found that deans generally favored RCM. Indeed, each of the three deans noted that they favored RCM over the incremental budget model UMTC maintained previously. Additionally, the deans indicated that RCM provided a clear accounting of budgetary issues regarding revenues and cost, which helped them implement academic reforms (Hearn et al., 2006). Deans also reported that RCM created awareness of the cost implications of their colleges' activities (Hearn et al., 2006). However, despite several successes, deans expressed concerns regarding RCM's impact on the overall university's mission. Additionally, the deans indicated that they were unaware of how or to what extent RCM impacted the university's effectiveness and efficiency (Hearn et al., 2006).

Hearn et al.'s (2006) study is limited in at least two ways worth noting. First, Hearn et al.'s (2006) use of descriptive analysis was inadequate to investigate the extent to which RCM impacted student enrollment and the number of credit hours taught across the colleges at UMTC. Specifically, the researchers did not employ a causal or quasi-experimental method to appropriately attribute RCM to the changes in enrollment and credit hours taught. The findings regarding enrollment and credit hours taught would have been better supported if an appropriate technique such as synthetic control methodology (which will be discussed in *Chapter 3: Methodology*) had been used.

Secondly, Hearn et al.'s (2006) study documents deans' mixed feelings regarding the effectiveness of RCM at UMTC. However, Hearn et al. (2006) only interviewed three deans. At the time of the study, UMTC enrolled over 50,000 students within 21 colleges. The findings would have been most robust if the scholars had interviewed more deans regarding their experiences with RCM.

In another study, Gros Louis and Thompson (2002) conducted a secondary analysis of Indiana University-Bloomington's (IUB) internal reviews of RCM and found that IUB's experience with RCM over ten years was also mixed. Using internal institutional documents, budget reports, and the five-year and ten-year internal reviews of RCM, the researchers revealed that the RCM Review Committees' (composed of faculty, staff, and administrators) perceptions of RCM were both positive and negative.

For example, Gros Louis and Thompson (2002) indicated that some committee members perceived positively of RCM for at least three reasons: first, RCM provided financial flexibility for administrators to meet students' needs; second, RCM created incentives for income generation and long-term planning; and third, RCM fostered partnerships between faculty and administrators – specifically, RCM helped units become more engaged in decision making because it encouraged collaboration.

On the other hand, Gros Louis and Thompson (2002) noted that some RCM committee documents indicated that faculty and administrators believed that RCM reduced academic quality. Specifically, some faculty believed that when part-time instructors were employed to teach courses, the instructors would be less rigorous than full-time professors. Additionally, regarding academic quality, some IUB faculty felt RCM encouraged grade inflation because RCM promoted revenue growth through course



enrollment. Specifically, it was suggested by some IUB faculty that other faculty members would inflate grades in order to generate more student demand for their courses. The scholars noted that the academic quality and grade-inflation speculations were unsubstantiated. However, the authors did not indicate what analysis was done to test or negate those speculations. Thus, the extent to which RCM impacted academic quality remained inconclusive.

In addition to academic quality and grade-inflation perceptions, faculty and administrators indicated that RCM did not provide a method for controlling costs (Gros Louis & Thompson, 2002). For example, in the 1999-2000 university review of RCM, the committee noted that deans struggled with controlling instruction costs (Gros Louis & Thompson, 2002). Specifically, it was difficult to discern when a permanent instructor should be hired versus hiring part-time instructors. At that time, the researchers noted that enrollment had fluctuated, and state funding was flat or declining in some years. Therefore, departments were reluctant to hire permanent faculty due to the uncertainty of student demand and financial resources. Additionally, Gros Louis and Thompson (2002) noted that some faculty and administrators perceived that RCM reduced collegiality between schools and colleges: RCM deemphasized cooperation and collaboration. The scholars suggested that this connection between RCM and cooperation was also unsubstantiated.

Deering and Sá (2018) found evidence to support the claims made in Gros Louis and Thompson (2002) by IUB faculty regarding RCM's impact on collegiality. Specifically, Deering explored the relationship between unit autonomy and coordination at four RCM universities: two in Canada and two in the United States. The two research-

intensive universities were the University of Michigan (UM) and the University of Toronto (UT). The two comprehensive institutions were the University of Lethbridge (UL) and the University of New Hampshire (UNH).

Deering and Sá (2018) found that RCM can negatively impact lateral coordination (i.e., the alignment between academic units to develop multidisciplinary programs, create joint appointments of faculty, etc.), and vertical coordination (i.e., the coordination among academic units in relationship to the university's overall mission and goals). Deering and associates examined autonomy and coordination based on differences with regard to how each of the institutions operated RCM. In other words, the researchers sought to uncover how the various RCM funding formulas and revenue and cost allocation rules might have impacted how internal academic units interacted with each other and with central administrators. The scholars analyzed institutional documents (e.g., budget documents, documents from external debt rating agencies, state and federal higher education finance reports, national faculty association reports). They also interviewed 55 senior administrators and faculty administrators at the four universities. Three findings are worth noting: first, the two research institutions (UM and UT) possessed high levels of coordination – lateral and vertical. Specifically, the RCM funding formulas and allocation rules at UM and UT allowed academic units to be autonomous (i.e., due to the devolution of budget authority to the deans) but also beholden to the goals of their institutions (i.e., due to the use of discretionary funds held by central administrators to incentivize collaboration). More specifically, the central administrators at UM and UT were described by interviewees as ‘hands-off’ – meaning that deans were given wide latitude to lead their units. Despite giving deans wide latitude, the RCM funding formulas

allowed central administrators at UM and UT to generate and maintain a discretionary fund that was subsequently used to steer their respective institution (i.e., to incentivize behavior among the academic units through investment into new and innovative programs) (Deering & Sá, 2018).

In contrast, Deering and Sá (2018) revealed that UL and UNH possessed low levels of coordination. Specifically, the authors described RCM at UL and UNH as overly decentralized. For example, deans at UL and UNH were given wide discretion in decision making. This was evidenced by their RCM funding formulas – specifically, the central administrations at UL and UNH did not retain a significant share of revenues (i.e., a discretionary fund like UT and UM) to steer the institution (Deering & Sá, 2018). Instead, the majority of revenues from government appropriations, tuition and fees, and research at UL and UNH were allocated to the academic units. As a consequence, central administrators at UL and UNH were unable to influence decision making among the academic units. Moreover, the lack of influence by central administrators also disincentivized academic units to work collaboratively with each other in the achievement of broader institutional goals (e.g., developing interdisciplinary programs, reducing the duplication of services, etc.). Deering and Sá (2018) concluded that RCM can negatively impact coordination at institutions. As shown in the cases of UL and UNH, poor coordination can result in conflict, competition, and inefficiencies.

Despite revealing differences in autonomy and coordination between the two sets of universities in the study (i.e., UT and UM compared to UL and UNH), Deering and Sá's (2018) study is limited in at least three ways. First, the study would have been more robust if the authors provided information on the RCM budgeting formulae and resource

allocation rules for each of the institutions in the study. For example, the study revealed that deans at UT and UM were autonomous – specifically, their autonomy was due to the RCM funding structures that allowed deans to make financial decisions and contribute to the overall mission of the institution. However, the question of “how” the RCM budgeting formulae and allocation rules were structured was not discussed.

Secondly, Deering and colleagues’ (2018) study is limited because the scholars did not provide sufficient institutional contexts around each of the four universities in the study. For example, the authors indicated that large research universities (i.e., UT and UM) possessed similar characteristics as it relates to autonomy and coordination. However, it would have improved the study to know how and to what extent UT and UM may have differed. Similarly, for the other institutions in the study (i.e., UL and UNH), it would have strengthened the study to know how the institutions differed. Specifically, what allowed UL and UNH to become overly decentralized? Was the overly decentralized nature of UL and UNH by design or by accident? Conversely, what components of each institution’s background and context facilitated coordination at UT and UM? These questions were not addressed.

Lastly, Deering and Sá’s (2018) study is limited because the reader is not made aware of when each institution adopted RCM, or if the people that were interviewed for the study were employed before each institution switched budget models. This information would have provided more clarity and credibility to how interviewees explained their experiences with regard to RCM, specifically, regarding how each of their universities may have changed as a result of RCM implementation.

Previously discussed studies (Gros Louis & Thompson, 2002; Hearn et al., 2006; Lang, 2002) revealed mixed experience regarding RCM *within* the institutions. However, Deering and Sá (2018) found mixed experiences regarding RCM *across* the institutions. UM and UT realized higher levels of coordination compared to UL and UNH. Higher levels of lateral and vertical coordination, as noted by Deering and Sá (2018), resulted in schools and colleges within UM and UT working collaboratively to achieve their respective university's mission. However, Deering and Sá (2018) indicated that RCM negatively impacted coordination at UL and UNH. As a consequence, schools and colleges within UL and UNH were less inclined to achieve their respective university's mission. Instead, Deering and his associate suggested that the lack of coordination resulted in competition and distrust. Thus, the authors concluded that central administrators must develop coordination mechanisms (i.e., similar to UM and UT) in order to minimize the risk of unintended consequences that were experienced at UL and UNH.

### **Additional Empirical Findings Regarding RCM**

Other empirical studies on RCM have provided additional nuance to our knowledge of RCM; however, these studies (Cekic, 2010; McBride et al., 2000; Rutherford & Rabovsky, 2017) are not directly tied to the general lines of inquiry discussed above. Specifically, these studies (Cekic, 2010; McBride et al., 2000; Rutherford & Rabovsky, 2017) do not examine institutions' motivations for adopting RCM nor do they document institutional experiences with RCM.

## **RCM Budgeting is a Structural Process**

Cekic (2010), in a 15-year case study, investigated how faculty and administrators' decision-making processes for budgeting changed after the implementation of RCM at Indiana University-Bloomington (IUB). The researcher used Bolman and Deal's (2003) four organizational frames (i.e., structural frame, human resource frame, political frame, and symbolic frame) to analyze 36 interviews (i.e., 15 interviews in 1988-89, 13 interviews in 2001, and eight in 2006) and identify which frames, if any, were most prevalent in the budget and planning processes. The structural frame focuses on bureaucracies, rules/policies, and institutional goals (Bolman et al., 2003 as cited in Cekic, 2010). The human resource frame centers around interpersonal relationships, needs, and skills of the people within the organization (Bolman et al., 2003 as cited in Cekic, 2010). The political frame focuses on power, competition, and negotiation (Bolman et al., 2003 as cited in Cekic, 2010). Lastly, the symbolic frame revolves around ceremonies, traditions, and institutional stories (Bolman et al., 2003 as cited in Cekic, 2010).

Cekic (2010) argued that RCM was a product of a market-interaction paradigm. This suggested that resource allocation decisions under RCM should be based on political interactions that result in the greatest good for the most people. Thus, the author hypothesized that RCM budgetary decision-making at IUB would be consistent with Bolman and Deal's (2003) political frame. Cekic found that faculty and administrators predominantly used the structural frame in budgetary decision-making. To explain the salience of the structural frame in the findings, the researcher noted that the budgeting process at IUB was historically identified as a political process. Specifically, IUB's old

budget model – the incremental model – created competition due to the scarcity of resources and central administration’s responsibility to allocate all resources across the entire campus. However, with the implementation of RCM – which emphasized information-rich and data-driven processes – resource allocation decisions became more consistent with Bolman and Deal’s structural frame (Cekic, 2010). That is, RCM provided deans with financial responsibility, incentives, and processes (i.e., funding formulas) to mitigate the need to exert power or engage in competition for resources. For example, one of the interviewees stated:

One of the things I like about RCM is; the [formulas] drive [the budgeting process]; so much in RCM in this transparent way that I think it minimizes the contests. ... I mean, there are politics and there are contests, but ...these kinds of regulations, these models or the rules of RCM ... leave a lot less room to kind of argue over resources (Cekic, 2010, p. 94).

This finding has at least two implications: first, RCM impacted how IUB faculty and administrators viewed the budgetary process; and second, faculty and administrators at IUB felt less inclined to compete for resources under RCM versus their need to compete for resources under the incremental model. Although the budgeting and planning processes at IUB were most consistent with the structural frame, other studies have not examined the change in the decision-making process under RCM using Bolman and Deal’s (2003) four frames of organization culture. Thus, the main result from this study is isolated. Perhaps a comparative examination of this phenomenon across multiple institutions would have strengthened this study and provided more insight regarding how faculty and administrators view their budget responsibilities under RCM.

## **RCM Impacts Faculty Workload**

McBride et al. (2000) examined RCM in relation to faculty time and effort at Indiana University-Purdue University Indianapolis' (IUPUI) School of Nursing. The goal of the project was to estimate how RCM impacted faculty time and effort. As a part of the project, faculty at the School of Nursing were surveyed in 1993-94 and again in 1997-98 to assess how they allocated their time as a faculty member. Between the two survey periods (i.e., the first in 1993-94 and the second in 1997-98), McBride et al. (2000) analyzed differences in how faculty responded. For example, the average percent of faculty time spent on administration (e.g., program management, strategic planning, management of fiscal affairs, fundraising, faculty development, etc.) decreased from 14.3% to 14% between 1993-94 and 1997-98. The average percent of the faculty's time on instruction decreased from 54.6% to 48.8% between the same time frame. The average time spent on unfunded service (e.g., writing grant proposals, peer-reviewing articles, writing book chapters, etc.) decreased from 7.3% to 6.5%. However, the average percent of faculty time spent on research and faculty development increased between the same four years. Specifically, the average time spent on funded research increased from 18% to 22.4%; and the average time spent on unfunded research rose from 3.5% to 5.8%.

Although the findings from McBride et al. (2000) suggest that RCM impacted how faculty spent their time at IUPUI, the study is limited because the researchers did not conduct an analysis to show if (or to what extent) their results might have been changed in the absence of RCM. Specifically, the descriptive methods employed by the researchers do not causally link RCM to the changes in faculty time. Additionally, McBride et al. (2000) do not report the sample size of the survey respondents nor do the



authors specify if the same survey respondents were surveyed in 1993-94 and 1997-98. This casts doubt on how much, if any, faculty changed how they allocated their time since there could have been different respondents in each survey period. The study would have been enhanced if the scholars had relied on quantitative methods such as difference-in-differences or synthetic control methodology (i.e., both methods will be described in *Chapter 3: Methodology*) to determine whether RCM *impacted* faculty time and effort at work. Moreover, the study could have been strengthened if the scholars included other schools/colleges within IUPUI for comparative purposes. This would have provided readers with a sense of magnitude regarding RCM's potential impact across IUPUI's campus versus its impact at one school/college.

### **RCM Affects Graduation Rates**

Rutherford and Rabovsky (2017) examined the effect of RCM on two outcomes: undergraduate graduation rates and degree production at four-year public and private research universities. The sample consisted of 276 public and private research universities in the United States, 32 of which had implemented RCM by 2013. The authors defined graduation rates as the percentage of first-time freshmen who graduate within six years. They used a dummy variable to signify whether an institution used RCM. The panel data for graduation rates ranged from 1991 to 2009. Using fixed-effects regression, the authors found a positive significant relationship between graduation rates and the use of RCM. Further analysis revealed a statistically significant relationship between graduation rates for white students and the use of RCM (Rutherford & Rabovsky, 2017). However, no significant relationship was found for Black or Hispanic students' graduation rates.

Regarding the second outcome, degree production, Rutherford and Rabovsky (2017) did not find a significant relationship between the use of RCM and degree production. This suggests that RCM institutions might be doing more to get students to graduation faster and perhaps more efficiently. While this may be the case, the finding regarding degree production evinces that RCM institutions are not necessarily producing more degrees than non-RCM universities, on average. This study is one of two that has employed an advanced quantitative technique to analyze RCM's impact. However, Rutherford and associate's study has several limitations that will be examined in a separate section. (see *Gaps and Limitations* further below.)

### **Summary of Scholarship on RCM**

Researchers have not systematically investigated RCM, thus leaving the body of scholarship disparate and scant. Few general findings have emerged as a consequence. Specifically, the empirical literature on RCM has revealed only two broad findings and several disparate findings on RCM's impact thus far. Moreover, most research findings on RCM are institution- and context-specific (i.e., not generalizable) because scholars have mostly examined RCM using small-sample case study research designs. Case study methods have been appropriate to explore the "how" and "why" questions regarding RCM – specifically to understand the contextual factors and stakeholders that are affected by RCM, such as the people (e.g., administrators, faculty, staff, and students) and the processes (e.g., budgeting processes, funding formulas, accounting systems). The use of document analysis and interviews within the qualitative case studies has been appropriate to assess how RCM impacts people and the processes.

However, few empirical studies have examined the “what” and “to what extent” questions regarding RCM’s effect on financial outcomes (i.e., revenues). Perhaps the most obvious omission in the literature, prior to this study, was an examination on the extent to which RCM impacts costs, given the emergence of RCM adopters since the Great Recession in 2008 and the number of institutions that have adopted RCM primarily to control costs (Deering & Sá, 2014; Jaquette et al., 2018). A synthesis of how scholars and economists have studied higher education costs is next.

### **Scholarship on Higher Education Costs**

Unlike the paucity of the empirical literature on RCM, scholarship on higher education costs is voluminous. Researchers have extensively theorized and empirically assessed the nature of costs in higher education (Baumol & Bowen, 1966; Bowen, 1980; Winston, 1999). Within these domains, scholars have provided insight into three broad lines of inquiry: (1) to explain why higher education costs rise faster than costs in other industries; (2) to identify opportunities for efficiencies within and across colleges and universities; and (3) to understand the relationship between revenues and costs among higher education institutions.

### **Theoretical Perspectives on Costs in Higher Education**

My review of the literature revealed four major theories that undergird research into why higher education costs rise faster relative to costs in other industries: Baumol and Bowen’s (1966) Cost Disease Theory, Bowen’s (1980) Revenue Theory of Costs (RTC), the Positional Arms Race Theory, and Principal-Agent Theory (PAT). Debates remain ongoing regarding which theory most closely describes why higher education

costs continue to rise (Archibald & Feldman, 2008, 2018; Cheslock et al., 2016; Kimball et al., 2018; Martin & Hill, 2014). A brief overview of each theory is presented below.

### **Cost Disease Theory**

The cost disease theory was developed by Baumol and Bowen (1966) seeking to explain cost escalation in the performing arts industry. Baumol and Bowen explained cost disease theory by drawing a distinction between two industries: goods-producing industries (e.g., manufacturing) and the personal services industry (e.g., performing arts, health care, and education). The fundamental distinction between the two industries is that goods-producing industries use labor to make a product – that is, labor is a component of what produces a good, such as a car for example. However, in the personal services industries, labor is the final product. For example, a flutist’s time (labor) playing the flute in an orchestra is the final product.

Cost disease theory posits that costs in goods-producing industries rise slower than costs in personal services industries because personal services industries do not benefit from productivity increases (Baumol, Blackman, & Wolff, 1985; Baumol & Bowen, 1966). For example, technological advancements in goods-producing industries such as automobile manufacturing have increased productivity. These advancements, in turn, have allowed many goods-producing industries to save on labor costs. For example, with the procurement of a new piece of equipment (i.e. technological advancement), a car manufacturer may be able to produce ten times more vehicles with fewer staff. Thus, the manufacturer is able to become more productive and save on labor costs by leveraging technology. On the other hand, cost disease theory suggests that personal services industries like higher education have not realized the same experiences with regard to

productivity for at least three reasons. First, advancements in technology in the higher education sector have not been able to replace or substitute the need for highly educated instructors. Second, the time it takes for instructors to provide higher education has remained relatively the same – that is, it still takes an instructor three hours to teach a three-hour lecture. Lastly, the average class sizes (i.e., faculty-student ratios) have remained relatively the same as they were decades ago, thus faculty are not educating significantly more students than in previous decades (Archibald & Feldman, 2008, 2018; Cheslock et al., 2016). Because the price of labor grows year over year irrespective of productivity growth, labor costs in personal services industries, theoretically, rise faster than goods-producing industries because personal services industries do not benefit from productivity gains (Cheslock et al., 2016). Therefore, the cost disease is one that, in theory, cannot be ‘treated’ without productivity increases (Baumol et al., 1966).

Scholars (Archibald & Feldman, 2008, 2018; Kimball et al., 2018; Martin & Hill, 2014) have debated whether the cost disease theory appropriately describes cost escalation in higher education. On one hand, researchers (Archibald & Feldman, 2008, 2018) have found evidence to support cost disease theory. For example, Archibald and Feldman (2008) conducted a study to measure the differences between higher education costs relative to costs from other industries (i.e., other personal services industries as well as non-personal services industries). Archibald and Feldman (2008) sought to investigate cost disease theory compared to the revenue theory of cost to discern which theory better described cost fluctuations across industries. Using data from 1949-50 to 1995-96 to measure the absolute and average absolute deviations between prices of other industries and the corresponding costs of higher education, Archibald and Feldman (2008) found

that costs in higher education behaved much more similar to costs in industries providing services rather than goods-producing industries. Moreover, among the service industries, the scholars found that higher education costs were similar to the costs of services provided by highly-educated workers compared to the costs of the services provided by workers with lower levels of education (Archibald & Feldman, 2008). These findings were consistent with the cost disease theory for at least two reasons. First, higher education costs (and the costs of other personal services industries) rise faster than the costs in goods-producing industries. Second, within the personal services industries, higher education costs rise more consistently with other services industries that require highly educated labor (Archibald & Feldman, 2008).

Other scholars (e.g., Kimball et al., 2018) maintained an opposing view with regard to cost disease theory. In a historical analysis and investigation on cost disease theory, Kimball et al. (2018) rejected Archibald and Feldman's (2008) validation of cost disease theory for at least two reasons. First, Kimball et al. (2018) argued that Archibald and Feldman (2008) incorrectly dichotomized the distinctions between cost disease theory and the revenue theory of cost. For example, Archibald and Feldman (2008) hypothesized that if the revenue theory of cost better represented higher education cost escalation, then the analysis of higher education costs would follow an arbitrary path over time. However, if the results were better described by the cost disease theory, then the analysis would show that higher education costs follow a similar time path as other service industries. Because Archibald and Feldman (2008) found that higher education costs were similar to other service industries, they concluded that the cost disease theory better described cost escalation in higher education. Kimball et al. (2018) contend that

Archibald and Feldman's (2008) analysis failed to consider whether the revenue theory of cost could be applied to other industries – specifically, Kimball et al. (2018) suggest that Archibald and Feldman's (2008) study was weakened because they incorrectly imputed the revenue theory of cost.

Secondly, Kimball et al. (2018) further concluded that the service industries – whose costs followed a consistent path as higher education costs in Archibald and Feldman's (2008) analysis – did not conform to the personal services industries as described by cost disease theory. Of the 18 service industries in which Archibald and Feldman (2008) found to be consistent with higher education cost escalation, Kimball et al. (2018) identified nine that were not personal service industries. Some of the nine non-personal services included: “water and other sanitary services, mass transit systems, [and] rent of tenant-occupied nonfarm dwellings” to name a few (Kimball et al., 2018, p.43). Therefore, Kimball et al. (2018) rejected cost disease theory as a viable perspective to describe higher education costs.

### **Revenue Theory of Cost**

Unlike cost disease theory, which emphasizes how external market forces impact cost escalation in higher education, specifically labor costs, Bowen's (1980) revenue theory of cost (RTC) contends that cost escalation is internal to higher education. Specifically, RTC posits that colleges and universities are not revenue maximizers, or cost minimizers like private-sector firms. Instead, RTC suggests that colleges and universities function with the goal of maximizing their prestige, excellence, and influence. Specifically, colleges and universities raise as much money as they can; and then spend all of the money they raised on factors that contribute to their prestige,

excellence, and influence (Bowen, 1980). However, there is no discernable way to identify when an institution has maximized its prestige, excellence, or influence. Therefore, an institution's total costs are only bound by its total revenue. This means that institutions will incessantly spend on prestige-maximizing elements until revenues are depleted (Bowen, 1980). Therefore, RTC suggests that cost escalation in higher education is the result of institutional choice rather than a result of stagnant productivity as suggested by cost disease theory (Archibald & Feldman, 2008; Bowen, 1980; Martin, 2011; Martin & Hill, 2014).

Scholars (Archibald & Feldman, 2008; Martin & Hill, 2014) have found mixed evidence with regard to whether cost disease theory or RTC better describes higher education cost escalation. Archibald and Feldman (2008) concluded that the cost disease theory better illustrated why costs rise in higher education in their analysis of costs in other industries. In a different study that investigated cost disease theory compared to the revenue theory of cost, Martin and Hill (2014) found little evidence to conclude that cost disease theory better described cost increases in higher education. Instead, Martin and Hill (2014) concluded that the revenue theory of cost better represented cost escalation in higher education, arguing instead that higher education cost drivers were internal. Specifically, Martin and his associate estimated average cost functions for public and private research universities using data from two distinct periods: the first period was described as the "loose revenue constraints" period (i.e., 1987 to 2005); and the second period was described as the "tight revenue constraints" period (i.e., 2008 to 2011). To examine cost disease and RTC, the authors theoretically framed cost disease theory using average faculty salary and benefits (i.e., since the crux of cost disease theory focuses on



labor costs). The researchers included average faculty salary and benefits, in addition to variables that accounted for revenue sources (i.e., since RTC suggests that universities raise all the money they can and spend all the money they raise). The authors found that the effects explained by RTC were larger than those explained by the cost disease theory during both periods: the loose revenue constraints period and the tight revenue constraints period (Martin & Hill, 2014). Specifically, the researchers found that college and university costs in both periods were more consistent with what available revenue (i.e., RTC) versus costs being solely driven by labor costs (i.e., cost disease).

Leslie, Slaughter, Taylor, and Zhang (2012) tested RTC when examining revenue-expenditure relationships at 96 research-extensive universities in the United States. Data were drawn for 24 years (1984-85 to 2007-08) to investigate how public and private institutions utilized their various sources of revenue to carry out their missions. For public universities, revenue variables included: tuition, state appropriations, grants and contracts, gifts, sales, and other revenues. Expenditures variables included: instruction, research, public service, academic support, student services, institutional support, and scholarships. Variables for private universities included the same revenue and expenditure variables as the public universities, with the exclusion of state appropriations as a source of revenue.

Leslie et al. (2012) focused mostly on the revenue relationship with two key expenditures: instruction and research because these two expenditures most closely represented the mission of research universities. Using ordinary least squares regression with fixed effects, the authors found that public universities' spending patterns behaved as would be expected – that is, a large proportion of tuition revenues were spent on

instruction. More specifically, for each dollar increase in tuition revenue received by public institutions, they spent almost 46 cents on instruction and 11 cents on scholarships (Leslie et al., 2012).

Private universities, however, followed a different path. Leslie et al. (2012) found evidence to support RTC, specifically with regard to private universities but not public universities. Specifically, the authors suggested that private research universities' spending conformed with RTC in two ways. First, the authors found that private universities spent a larger share of their largest source of revenue (i.e., tuition) on scholarships for students compared to public institutions. This suggests that private universities are intentionally raising and spending money to maximize their prestige by increasing the number of scholarships they could extend. Second, Leslie et al. (2012) found that for every dollar of grant and contract monies received by private institutions, they spent about 29 cents more of their own funds on research than did public research institutions. This finding is consistent with previous research on prestige maximization (that will be discussed in the next section), which suggests that institutions spend and invest in research to enhance their reputation, influence, and ranking (Melguizo & Strober, 2007; O'Meara, 2007).

### **The Positional Arms Race Theory**

The positional arms race theory (Cheslock et al., 2016; Melguizo & Strober, 2007; Winston, 1999) similar to RTC, suggests institutions seek to maximize their prestige. Consequently, cost escalation is a matter of institutional choice. Specifically, the positional arms race theory posits that higher education costs increase rapidly as a result of colleges and universities engaging in a competitive race for higher rankings

(Cheslock et al., 2016). The college rankings in *U.S. News & World Report* (USNWR) – among other sources of college rankings – play a crucial role in the competition between institutions (Cheslock et al., 2016; O’Meara, 2007; Winston, 1999). For example, USNWR rankings take into account several measures to calculate an institution’s ranking, including academic reputation (25%); the retention rates of undergraduate students (25%); faculty resources, such as faculty compensation and average faculty-student ratio (20%); student selectivity based on college admissions exams (15%); education expenditure per student (10%); and alumni giving (five percent) (Melguizo & Strober, 2007). Scholars argue that institutions make significant financial investments in each of the USNWR categories in pursuit of prestige and position. Put another way, colleges and universities spend more to attract the best faculty, students, and resources (e.g., research grants, campus amenities, student services, etc.) in order to climb the rankings (Melguizo & Strober, 2007; O’Meara, 2007; O’Meara & Meekins, 2012). As a consequence of the pressure placed on institutions to climb the rankings (and the incessant spending in the pursuit of prestige), higher education costs have risen, according to the positional arms race theory.

Winston (1999) suggests that institutions differentially engage in the positional arms race. For example, he notes that colleges and universities at the top of the rankings compete for the highest quality of students and faculty; and institutions at the bottom of the rankings compete for students who are willing to “buy” their product (i.e., enroll in their institution) because there is less demand (Winston, 1999). However, Winston (1999) argues that institutions’ ability to compete for positions is predicated on each of their donative resources (i.e., available revenue from private sources). Therefore, he contends

that most institutions are often at the beginning or at the end of fundraising campaigns so that they can recruit students (i.e., using institutional financial aid and state of the art amenities), faculty (i.e., through lucrative salaries and start-up packages), and additional resources that would increase the institutions' excellence, prestige, and position (Winston, 1999).

O'Meara (2007) identified and listed several "striving" characteristics to illustrate some of the financial and organizational changes made by institutions that are engaged in the positional arms race. In part, many of the characteristics showcased a need for increased spending for several purposes: to recruit academically talented students; to recruit and retain high-profile faculty members; to modify and enhance curriculum and program offerings; to increase the number of graduate programs, and to make external/structural changes on campus (O'Meara, 2007).

Several scholars (Kim, 2018; Melguizo & Strober, 2007) have empirically tested components of the positional arms race theory. For example, Melguizo and Strober (2007) examined the relationship between prestige maximization and faculty salaries. The authors hypothesized that prestige-maximizing institutions would reward faculty through compensation increases for enhancing the institution's reputation through research. Moreover, because faculty compensation accounted for a portion of ranking calculations, the scholars suggested that if faculty spent more time publishing research, faculty would be rewarded financially while also helping the institution to rise in the rankings. Overall, the researchers found a positive significant relationship between faculty research activity (i.e., the prestige-maximizing construct) and faculty salary. These findings were consistently positive and significant across institution type (i.e.,

research, doctoral, and liberal arts) and across disciplines (i.e., natural sciences, engineering, professional fields, social sciences, education, and humanities). The scholars found no evidence to show that faculty salaries had been impacted by the faculty's time spent on teaching. Thus, the scholars found evidence to support a component of the positional arms race theory – specifically that institutions, in an effort to maximize their prestige (and ranking by extension), have rewarded faculty for contributing to activities that enhance prestige such as research.

Kim (2018) examined how USNWR rankings impacted operating expenditures across two groups of institutions established by USNWR: the National Universities and National Liberal Arts Colleges. Kim revealed that USNWR rankings significantly impacted expenditures at National Universities and National Liberal Arts Colleges, however, the nature of spending across these groups was different. After moving from a non-ranked position to a ranked position in the top 25, 50, or 120, the National Universities increased instructional expenses by 3.1% within two years and 8.9% for three years and thereafter (Kim, 2018). The National Liberal Arts Colleges, on the other hand, significantly increased spending in education-related and non-instructional support (Kim, 2018). Kim did not find evidence that the National Liberal Arts Colleges increased spending on research.

### **Principal-Agent Theory**

Principal-agent theory (PAT) is another perspective used to describe why costs rise in higher education. PAT originated in economics and has been applied to political science and higher education. PAT focuses on a contractual relationship between two or more entities, whereby the *principal* contracts the services of an *agent* to perform certain

functions (i.e., services that require specialized knowledge not possessed by the principal) that will improve the condition of the principal (Cheslock et al., 2016; Lane & Kivisto, 2008). The nature of the contractual relationship can be explicit – where there is a formal agreement; or implicit – where there is a common understanding that the agent will perform certain functions in the interest of the principal. However, PAT posits that higher education costs rise because the goals of the principal will differ, in part, from the goals of the agent, such that the agent will work in his/her/its own self-interests and towards his/her/its own goals. This is defined as *shirking* (Kivisto, 2005, 2008; Lane & Kivisto, 2008). PAT suggests that principals develop incentives to mitigate shirking. These incentives can be rewards-based – that is, to reward acceptable behavior. Additionally, the incentives can be punitive/sanctions-based, to disincentivize unacceptable behavior. Applied to higher education, Lane and Kivisto (2008) indicated that PAT can involve multiple principals and multiple agents. For example, Martin (2011) described the principal-agent relationship between students, parents, and taxpayers (i.e., the principals) and faculty, staff, and administrators (i.e., the agents).

Martin (2011) suggests that costs in higher education rise because agents seek to achieve different goals than the principals. For example, faculty at a research institution may value research over teaching. However, students and families may value teaching over research. As faculty partake in more research projects, the institution may need to hire additional teaching staff. This, in turn, has cost implications for both the principals and the agents. Regarding the agents, as a result of focusing more on research, there may be additional administrative requirements and costs necessary to secure or maintain grant funding for the research projects.

Scholars (Jaquette et al., 2018; Tandberg et al., 2017; Titus, 2009) have used PAT to model various principal-agent relationships in higher education. Titus (2009) utilized PAT to examine the relationship between state governments (i.e., the principal) and institutions of higher education (i.e., the agents). Tandberg et al. (2017) used PAT to understand the relationship between governors (i.e., the principal) and the state higher education executive officers (i.e., the agents). Specifically, Tandberg and associates (2017) hypothesized that when a governor possesses significant institutional authority over the state higher education executive officer (SHEEO), the SHEEO would, in turn, align more closely with the governor's higher education spending priorities. Tandberg et al. (2017) found that when a governor possesses the authority to appoint a SHEEO, state spending on higher education increases. Theoretically, such an appointment authority gives colleges and universities more revenue to spend, which intersects with RTC as described above (i.e., colleges and universities raise as much revenue as they can and spend all that they raise).

Although Tandberg et al. (2017) did not use PAT to theoretically frame a principal-agent relationship within a college or university, the findings suggest that PAT, in combination with RTC, may be useful in explaining costs at the institutional level. For example, as noted above, the principal-agent relationship between governors and SHEEOs has implications on state spending for higher education. As state spending on higher education increases, public colleges and universities are theoretically given more revenue to spend. By possessing more revenue to spend, colleges and universities may be inclined to spend the additional revenue that they received – according to RTC. Specifically, RTC suggests that colleges and universities spend all the revenue they raise

(or receive from state sources). Therefore, a principal-agent relationship within an institutional context (i.e., within a college or university), may also impact revenue (and costs by extension) according to RTC. However, PAT in tandem with RTC has not been used to conceptually frame costs at the institutional level. This dissertation study uses PAT and RTC to fill this gap in the literature. (Further discussion on how PAT and RTC are used in this dissertation study is below in the Theoretical Framework section.)

Researchers have also used PAT to explain the principal-agent relationships within universities. Jaquette et al. (2018) utilized PAT to explain the relationship between central administration (i.e., the principal) and the deans of the academic units (i.e., the agents) in a study investigating RCM's impact on tuition revenue. The scholars suggested that RCM funding formulas and allocation rules were an incentive-based contract that bound the principal and agents in this context. Specifically, Jaquette et al. (2018) argued that central administrators cared most about generating additional tuition revenue, given the constrained financial reality of public higher education. Jaquette and associates asserted that the RCM funding formulas developed by central administrators would incentivize, and reward academic units to enroll more students, which would provide more tuition revenue by extension. They found that tuition revenue had significantly increased at three of the four institutions in the study and validated PAT's ability to explain the relationship between central administrators and deans who oversee RCM (Jaquette et al., 2018).

Despite revealing that PAT was a useful framework to elucidate RCM's positive impact on tuition revenue at three of the four universities in their study, Jaquette et al. (2018) did not investigate the extent to which the additional revenue generated by these



institutions may have impacted costs. This dissertation study examines RCM's impact on costs using PAT and RTC to account for the impact of revenue, including tuition revenue, on costs. (Further discussion on how PAT and RTC are used in this study is below in the Theoretical Framework section.)

### **Empirical Literature on Higher Education Costs**

In addition to the theoretical perspectives used to explain why higher education costs rise, scholars have identified factors that contribute to cost increases in colleges and universities. Indeed, over the last three decades, much of the empirical literature on higher education costs has employed statistical methods to explore and find differences within and across college and university cost structures. Specifically, most of the higher education cost literature has been guided by Baumol, Panzar, and Willig (1982). Baumol and associates argued that universities differ in terms of mission, size, research intensity, etc. As a result, Baumol et al. (1982) proposed three functional forms that have allowed scholars to model the cost of producing higher education. These functional forms include the constant elasticity of substitution, the quadratic fixed-cost function, and the transcendental function. The use of these statistical models has enabled researchers to model the multiple outputs produced by colleges and universities (e.g., instruction and research). As a result, scholars have found that institutional characteristics and activities drive cost increases in higher education. Brinkman (1990) revealed five determinants of costs among colleges and universities: size, scope, level of instruction (undergraduate versus graduate education), academic discipline (i.e., academic program mix), and revenues. These cost determinants, in addition to institutions' geographical/regional

locations, have been used to explain the cost of producing higher education (Cheslock et al., 2016).

### **Determinants of Costs in Higher Education**

Empirical research has documented several determinants of costs in higher education. Specifically, these studies have elucidated opportunities for efficiencies in higher education by (a) identifying economies of scale, which are present if an increase in any output such as enrollment would result in a decrease in cost; (b) identifying economies of scope, which are present if producing two or more products jointly (e.g., offering graduate education and undergraduate education) would decrease cost; and (c) assessing the extent to which colleges and universities are cost efficient, which estimates the minimum cost for producing a given level of outputs (Agasisti & Salerno, 2007; Brinkman, 1981; Brinkman et al., 1986; Cohn et al., 1989; deGroot et al., 1991; Doyle, 2010; Johnes & Schwarzenberger, 2011; Koshal & Koshal, 1999; Koshal et al., 2001; Kuo & Ho, 2007; Laband & Lentz, 2003; Mamun, 2012; Nelson & Hevert, 1992; Robst, 2001; Sav, 2004; Titus et al., 2017; Toutkoushian, 1999).

#### **Scale**

Institution size (i.e., scale) is seen by economists as its productive capacity and represents the level of outputs (e.g., number of students and class size) it produces (Brinkman et al., 1986). Researchers (Cohn et al., 1989; deGroot et al., 1991; Koshal & Koshal, 1999; Koshal et al., 2001; Laband & Lentz, 2003; Nelson & Hevert, 1992; Sav, 2004; Titus et al., 2017; Toutkoushian, 1999) have generally found positive returns to scale, which suggests that institutions of higher education, on average, could benefit from

modifying its scale (e.g., increasing enrollment or class size to reduce costs per student). For example, Cohn et al. (1989) investigated cost at 1,887 public and private institutions in the United States to identify economies of scale and scope. This study was the first to use a multi-product cost function to model the cost of producing higher education. The model assumed that higher education institutions' core mission is teaching, research, or a combination of both. Therefore, the scholars modeled total costs as a product of full-time equivalent (FTE) undergraduate enrollment, FTE graduate enrollment, and research expenditures (as a proxy for research). Cohn and associates found positive returns to scale. However, the returns to scale varied between public and private institutions – specifically, the authors revealed that economies of scale existed for research expenditures at public institutions, not private institutions, for example.

Although Cohn et al.'s (1989) study was among the first to model the cost of higher education as a multi-product function – which allowed the scholars to take into account the teaching and research components of institutions' missions – the study has three limitations. First, Cohn et al. (1989) only used one year of data across public and private universities. Subsequent research (as will be noted below) has revealed the importance of taking into account more than one year of data to increase the reliability and robustness of the findings. Secondly, Cohn et al. (1989) did not include variables to account for other factors that contribute to cost escalation, including academic program mix, class size, and institutions' locations. The inclusion of these additional factors would have strengthened the study and perhaps would have had implications on the results. Lastly, and perhaps most relevant to this dissertation, Cohn et al. (1989) did not consider if or to what extent institutions' budget models may have impacted their cost structures.

Several other studies (deGroot et al., 1991; Koshal & Koshal, 1999; Koshal et al., 2001; Laband & Lentz, 2003; Nelson & Hevert, 1992; Sav, 2004; Titus et al., 2017; Toutkoushian, 1999) have also found positive returns to scale but have not considered budget models in their analysis. For example, deGroot et al. (1991) investigated economies of scale and scope at 147 public and private research institutions in the United States. The scholars used one year of data from 1983. To model the cost of producing higher education, the researchers included total costs as the dependent variable and undergraduate FTE and graduate FTE as output measures for teaching. However, unlike Cohn et al. (1989) who included research expenditures as a proxy for research, deGroot et al. (1991) included the number of publications as a proxy for research. Additionally, deGroot et al. (1991) included average faculty and staff salaries as an additional input. deGroot et al. (1991) found positive returns to scale for all outputs (i.e., undergraduate enrollment, graduate enrollment, and research publications). Additionally, deGroot et al. (1991) found that graduate education was more costly than undergraduate education. Moreover, the authors revealed that institutions with a medical school had higher costs than those without. However, unlike Cohn et al. (1989), Koshal and Koshal (1999), and Sav (2004), deGroot (1991) did not find a significant difference in costs between public and private research universities.

Despite several contributions to research noted above, deGroot et al.'s (1991) study contains several limitations worth noting. For example, deGroot et al. (1991) include two questionable variables as proxies for research output and graduate education quality. Specifically, the authors use the number of publications as a proxy for research output at each of the institutions in the study. However, the researchers do not indicate

how publications were counted to generate the proxy for research output. Moreover, the scholars did not discuss the extent to which there may have been duplicate values in the number of publications. For example, if two faculty members at one institution co-authored one publication, would the publication count once or twice (i.e., one for each author)? Additionally, were the definitions for counting publications consistent across the institutions in the study?

With regard to the proxy for graduate education quality, deGroot et al. (1991) used a subjective five-point peer evaluation of graduate schools at each of the institutions in the study. This measure is perhaps problematic because it is not objective or consistent – specifically, the authors do not indicate how graduate schools were evaluated under the five-point system. Thus, the proxy for graduate education quality has external validity implications.

Additionally, deGroot et al.'s (1991) study is limited in similar ways as Cohn et al. (1989): (i) it also only considered one year of data; and (ii) it did not consider budget models, including RCM, in their analysis of higher education costs. As noted previously (and described below), the inclusion of more than one year of data provides more stability to the study and the subsequent results. Moreover, an examination of how costs are impacted by budget models, specifically RCM, is an open inquiry in which deGroot et al. (1991) did not consider but this study seeks to examine.

In a single-institution study, Nelson and Hevert (1992) analyzed economies of scale and scope at the University of Delaware. The authors used data from 31 departments across five years to model the cost of producing higher education at the institution. Specifically, the dependent variable was education costs defined as the sum of

each department's expenditures on professional, faculty, graduate teaching assistants, and staff salaries, including miscellaneous wages, supplies and expenses, occupancy and maintenance, equipment, and information processing (Nelson & Hevert, 1992). As a proxy for research, the researchers used faculty reports on the time they spent conducting research. Additionally, the authors included the outputs based on the credit hours taught across three categories: lower-level undergraduate teaching, upper-level undergraduate teaching, and graduate teaching. The researchers also included a control variable for average class size. In addition to several other findings that will be discussed below, the researchers revealed economies of scale – specifically, they found that marginal costs per student declined with increases in enrollment and with increases in class size (Nelson & Hevert, 1992).

Unlike the previously discussed studies (i.e., Cohn et al., 1989; deGroot et al., 1991), Nelson and Hevert (1992) analyzed data across five years versus one year. However, Nelson and Hevert's (1991) study is limited, in part, because the researchers only considered one institution. While there was considerable insight gained from this approach (i.e., considering only one institution versus multiple institutions), especially because other studies considered hundreds of institutions, Nelson and Hevert (1992) made unsubstantiated claims regarding the findings of this study. Specifically, the authors indicated that previous research on higher education cost had been mis-specified. However, because Nelson and his associate only considered one institution, the conclusions and analytic approach the researchers should not be extrapolated beyond the University of Delaware – the institution in which they examined. Additionally, similar to Cohn et al. (1989) and deGroot et al. (1991), Nelson and Hevert (1992) did not consider

how the budget model at the University of Delaware, for example, may have impacted costs across the five years of the study.

Koshal and Koshal (1999) analyzed economies of scale and scope at 329 public and private comprehensive universities in the United States using data from 1990-91. To model the cost of producing higher education, the authors used a statistical model where the dependent variable was total costs and the output variables were FTE undergraduate students, FTE graduate students, and research expenditures. Additionally, the scholars included control variables for institutions with Ph.D. students, the number of full-time faculty, average student-teacher ratio, average class size, and average faculty salary. The researchers also include a measure to account for the variation in the quality of the institutions – specifically, they use average SAT scores of the incoming freshmen class. Other researchers (Cohn et al., 1989; deGroot et al., 1991, etc.) had not used a measure for quality because they considered it difficult to measure. Koshal and Koshal (1999) found positive returns to scale for undergraduate FTE but diseconomies of scale for graduate FTE and research. Additionally, the researchers revealed that the cost of graduate education was higher than undergraduate education across public and private institutions. Moreover, the researchers evidenced that the marginal cost at private institutions was higher than at public institutions. Finally, the scholars revealed that class size impacted cost – that is, larger class sizes lower costs. All of these findings were mostly consistent with prior research. However, this study contains similar limitations as previously discussed studies (i.e., Cohn et al., 1989; deGroot et al., 1991). Specifically, Koshal and Koshal (1999) only considered one year of data across the institutions in the

study. Moreover, Koshal and Koshal (1999) did not examine how the budget models used across the universities in the study may have impacted costs.

Koshal et al. (2001) also only considered one year of data and did not examine the effects of budget approaches on costs at the institutions in the study. Specifically, in a study on 184 Bible colleges in the United States, Koshal et al. (2001) explored costs using data from 1994-95. Total cost was used as the dependent variable. Since Bible Colleges do not have an explicit research function, the authors only included undergraduate FTE and graduate FTE as outputs. In addition, the authors included average faculty and staff salaries, faculty-student ratio, and the average expense for instructional material per faculty member as control variables. Koshal et al. (2001) found economies of scale for undergraduate FTE but not for graduate FTE. The researchers also revealed that class size impacted costs, similar to previous research by Koshal and Koshal (1999).

Titus et al. (2017) examined cost efficiency at 252 public master's institutions in the United States. Titus and associates (2017) employed a multi-product function to model the cost of producing higher education. The dependent variable was measured by education and general expenses. The scholars included independent variables for undergraduate enrollment, graduate enrollment, research expenditures, average faculty salaries, faculty-student ratio, and control variables for historically Black colleges/universities, institutions with medical programs and hospitals, as well as institutions that award doctoral degrees. Using stochastic frontier analysis, the researchers revealed several results. First, the authors revealed economies of scale in undergraduate education and diseconomies of scale in graduate education. Secondly, the scholars also



evidenced that costs are regionally clustered and that cost inefficiency at master's institutions is long-term and persistent rather than short-term and residual. Lastly, and perhaps more generally, the scholars showed that few master's institutions are cost inefficient, suggesting that most master's colleges are cost efficient. However, the researchers did not consider if or to what extent budget approaches employed by the universities in the study may have contributed (or not) to their cost efficiency. The scholars noted, however, that future research should consider the effects of decentralized budget models such as RCM on cost. This study provides insight into this open inquiry – specifically in the context of RCM's impact on cost at public research universities.

### **Scope**

Researchers have also generally found positive returns to scope – that is, whether there are lower costs per unit when institutions increase the production of multiple outputs simultaneously, such as research and undergraduate education (Cohn et al., 1989; Koshal & Koshal, 1999; Koshal et al., 2001; Laband & Lentz, 2003; Sav, 2004; Toutkoushian, 1999).

In a study on cost efficiency across 1,492 private and 1,450 public institutions, Laband and Lentz (2003) found economies of scope for undergraduate education, graduate education, and research for public institutions. However, across private institutions in the study, the researchers revealed economies of scope for undergraduate education up to 250% of the mean, graduate education up to 100% of the mean, and research up to 400% of the mean (Laband & Lentz, 2003). deGroot et al. (1991) also found economies of scope among research universities. Specifically, the authors revealed

economies of scope for undergraduate and graduate education across the institutions in the study (deGroot et al., 1991).

Compared to the previously discussed studies, Laband and Lentz (2003) provided more insight regarding costs in relation to additional institutional characteristics such as: whether an institution is a land-grant institution, whether provides public service or has a medical school or hospital. However, the researchers, similar to the previously discussed studies, did not consider how budget approaches may have impacted costs at the institutions in the study.

Similarly, Sav (2004) examined costs at 2,189 private and public institutions using cross-sectional data from the year 1995. However, the scholar did not investigate how budget approaches such as RCM may have influenced costs. For example, to model the cost of producing higher education, the researcher used the number of undergraduate and graduate credit hours taught on a twelve-month production cycle, nine-month faculty salary, Carnegie classification, and geographical region. In addition to finding economies of scale across public and private institutions, Sav found economies of scope for undergraduate education at private comprehensive and baccalaureate colleges and universities. However, Sav found minimal evidence of economies of scope for public institutions. Additionally, Sav did not find significant economies of scope for graduate education or research across the institutions in the study.

### **Level of Instruction**

In addition to investigating and determining economies of scale and scope in higher education, researchers have shown that costs vary by level of instruction: undergraduate is less expensive to produce than graduate education (Brinkman, 1981;

deGroot et al., 1991; Koshal & Koshal, 1999; Koshal et al., 2001; Laband & Lentz, 2003; Nelson & Hevert, 1992). In an early study on research universities, Brinkman (1981) specifically examined factors that impacted instructional costs. Brinkman (1981) considered instructional costs at 50 institutions (29 public and 21 private) from one academic year, 1976-77. To model the cost of producing higher education, the researcher included instructional costs as the dependent variable. The author included the number of full-time faculty and the average faculty salary as input variables. Additional inputs included the number of non-faculty employees and a proxy for average salary. For outputs, the author used FTE enrollment for undergraduate and graduate students, the number of degree programs per FTE, and expenditures for sponsored research per full-time faculty member. Brinkman (1981) found that undergraduate and graduate enrollment positively impacted instructional costs across the institutions in the study. Moreover, Brinkman (1981) revealed that the marginal cost of graduate education was higher than the marginal cost of producing undergraduate education across public and private research universities.

However, despite showing early evidence that instructional costs vary by level of instruction, Brinkman's (1981) study is limited. First, the author only considered one year of data. Secondly, Brinkman (1981) only considered instructional costs at 50 research universities. However, during the period of the study, there were over 100 research universities, thus several were not included in the study. Lastly, and perhaps most relevant to this study, Brinkman (1981) did not consider how the budget models at each of the institutions in his study may have impacted costs.

Similarly, with regard to cost variation by level of instruction, deGroot et al. (1991) found that graduate education was four times more expensive than undergraduate education at research universities. This finding suggests that graduate education cross-subsidized undergraduate education. Specifically, the cost of undergraduate education may have been lowered as a result of courses being instructed by graduate students and non-tenured faculty. Koshal and Koshal (1999) also revealed that the cost of graduate education is higher than undergraduate education at public and private comprehensive universities. However, the authors also revealed variations by institutional control (public v. private). Specifically, the researchers found that costs at private institutions were higher than public institutions and that graduate education was double the marginal cost at private universities compared to public universities (Koshal & Koshal, 1999). Nelson and Hevert (1992) elucidated cost variations both across graduate and undergraduate education, but also within undergraduate education. Specifically, in their study on the University of Delaware, Nelson and Hevert (1992) showed that lower-level undergraduate courses were lower cost than upper-level undergraduate courses; graduate-level courses were the most costly, and all courses that possessed a lab component were more expensive than those that did not. Again, deGroot et al. (1991), Koshal and Koshal (1999), and Nelson and Hevert (1992) did not consider budget approaches, such as RCM, in their studies on higher education costs.

### **Academic Program Mix**

Researchers have also noted academic program mixes (e.g., science versus non-science programs) have cost implications. Specifically, the cost of teaching certain programs, typically science-based programs, are higher than non-science-based programs

(Agasisti & Salerno, 2007; Brinkman, 2000; deGroot et al., 1991; Johnes & Schwarzenberger, 2011; Kuo & Ho, 2007; Mamaun, 2012; Sav, 2004).

In two previously discussed studies (deGroot et al., 1991; Sav, 2004), the researchers found cost variations between institutions with medical and professional schools compared to those that did not operate medical or professional (post-baccalaureate) schools. Specifically, they revealed that institutions with medical and professional programs had higher costs than institutions without (deGroot et al., 1991; Sav, 2004).

Similar findings regarding levels of instruction exist in the international context as well. Agasisti and Salerno (2007) examined cost efficiency at 52 public Italian universities. The authors used a multiproduct function to model the cost of producing higher education. Specifically, they included student enrollment for graduate and undergraduate programs and research expenditures as a proxy for research output. Additionally, Agasisti and his associate parsed out graduate students based on the percentage of students who were doctoral students and based on those in scientific courses and those in non-scientific courses. The researchers grouped medical school and veterinary school students separately. Using data envelopment analysis on one year of data (i.e., from 2002-2003), the researchers found several mixed results. Generally, the scholars revealed that the larger institutions in the study were scaled efficiently. This means that the average costs of producing higher education were minimized based on the average enrollment across the institutions. However, those universities with medical programs, veterinary programs, and those with higher levels of Ph.D. students were less cost efficient (Agasisti & Salerno, 2007). The authors indicated that controlling for the

presence of science-based Ph.D. students and professional programs (e.g., medical and veterinary) proved useful in understanding cost efficiency variations across the institutions in the study. However, the study is limited because the authors did not investigate how the budget models of each of the 52 institutions in their study may have affected costs.

Kuo and Ho (2007) explored cost efficiency across 34 Taiwanese universities and sought to identify the effects of a new government funding system on cost efficiency. The scholars used data from 1992-93 through 1999-2000. Specifically, they included in their model: the number of enrolled undergraduates, graduate students, and research expenditures as the outputs. Additionally, the researchers included control variables to account for variations in academic programming at the institutions – specifically, they added a measure to capture the proportion of academic programs that were medicine, natural science, social science, engineering, as well as those with Ph.D. programs. They also included a control variable for the use of the new budget model. Generally, the scholars found that cost inefficiency had increased after the implementation of the new funding system. Additionally, the authors revealed diseconomies of scale for undergraduate enrollment and economies of scale for graduate enrollment and research. With regard to academic disciplines, Kuo and Ho (2007) discovered that institutions with a higher share of diverse programs realized higher costs.

Although Kuo and Ho (2007) examined higher education costs in the context of a new government funding system, the study is limited such that it did not consider how each institution individually responded to the new budget system. Specifically, Kuo and Ho (2007) showed that, on average, cost efficiency declined at the 34 institutions in the

study after the Taiwanese government imposed a new funding system that provided more discretion to campus leaders.

Johnes and Schwarzenberger (2011) examined cost efficiency at 72 German universities. The authors used stochastic frontier analysis to analyze the data. The dependent variable was total cost, which included personnel and other current expenditures. The output variables included: the total number of undergraduate and graduate students disaggregated by master's degree students and Ph.D. students. The scholars further disaggregated the data by parsing out science and non-science undergraduate and master's degree students. Research activity was measured by third-party research funding. Generally, Johnes and Schwarzenberger found that German institutions were cost efficient; however, there were significant differences across institutions. Specifically, the researchers found that technical universities (i.e., those with large science programs) had higher fixed costs and were less cost efficient compared to universities without technical programs. Moreover, the scholars found that science courses were the most costly to teach, and doctoral education was more costly than master's and bachelor's education. Additionally, master's education was more costly than undergraduate education. Lastly, the researchers found that institutions with specialized programs were less cost efficient than others with more diverse programs (Johnes & Schwarzenberger, 2011). The study is limited because it did not consider how budget approaches may have impacted costs at the institutions in the study.

## **Revenues**

Research has provided evidence that revenues, and their various sources, impact costs (Robst, 2001; Leslie et al., 2012). For example, in a five-year study on cost

efficiency at 440 public four-year institutions, Robst (2001) sought primarily to elucidate whether institutions who receive a larger share of state appropriations were more or less efficient than those that did not. Consistent with previous research, the scholar modeled the cost of producing higher education as a multi-product function. Specifically, he included: undergraduate enrollment, graduate enrollment, research expenditures, and faculty salaries variables to model higher education production. In addition, the researcher included revenue variables for tuition revenue and state appropriations, as well as control variables for Carnegie classification. Using stochastic frontier analysis, the author revealed that four-year public institutions were generally inefficient, even across Carnegie classifications. More importantly, the scholar found no significant differences between institutions with a smaller share of state appropriations compared to those with a larger share – that is, institutions with a small share of state appropriations were no more inefficient than those with a larger share. Moreover, the author also revealed that institutions that increased tuition revenue over the five-year period became more inefficient, however, changes in state appropriations did not affect cost efficiency. The author concluded that institutions with the smallest tuition increases became more efficient than those with larger tuition revenue increases.

Additionally, Leslie et al. (2012) examined the relationship between sources of revenue and functional expenditures across 96 public and private research-extensive universities in the United States. The authors focused on how sources of revenue impacted expenditures on instruction and research. They found that public research universities expended the majority of tuition revenue and state appropriations on instruction. Additionally, public universities spent the plurality of grants and contracts



revenue on research expenditures. However, private universities – who do not receive state appropriations – spent approximately the same proportion of tuition revenue on instruction as public universities. But private universities spent a higher portion of tuition revenue to support scholarships and fellowships for students compared to public universities. Moreover, private universities used a higher share of other revenue categories to support their research expenditures (Leslie et al., 2012). Although Leslie et al. (2012) accounted for many known factors that impact higher education costs (e.g., institution size, scope, revenues, etc.), the authors did not consider differences in institutional budget models such as RCM. This dissertation study addresses the gap regarding RCM and costs.

### **Location**

The literature has also examined the impact of colleges' and universities' locations on costs. For example, Toutkoushian (1999) studied economies of scale and scope in higher education. Specifically, he focused on 828 public and private four-year institutions that provided education to undergraduate and graduate students but did not operate a medical school. Using two different multi-product cost functions to model the cost of producing higher education, Toutkoushian developed one model that used total expenditures as the dependent variable and the second model that used expenditures per student as the dependent variable. Each model contained variables for undergraduate enrollment, graduate enrollment, research dollars received, the average full professor salary, student-faculty ratio, percentage of faculty who were full professors, percentage of expenditures for instruction, and a variable for public versus private control. Several of these variables were consistent with previously discussed studies. However,

Toutkoushian (1999) also included variables for geographic and urban location. Using multiple regression analysis, the author revealed several findings that were consistent with previous studies, including the existence of economies of scale for both public and private institutions; the cost of graduate education was higher than undergraduate education; private institutions have higher cost structures than public institutions; the average faculty salary had a positive significant relationship with expenditures, and the faculty-student ratio had a positive significant relationship with costs. This study also revealed cost variations by region – specifically, institutions in the New England and Far West regions had higher costs than those in other regions (Toutkoushian, 1999). Despite revealing the impact of institutional location on higher education costs, this study – consistent with all of the previously discussed studies on higher education costs – did not account for institutions’ budget models in his study. However, the author indicated that future researchers should consider investigating the impact of RCM on costs. This study addresses that gap in the literature.

Finally, Sav (2004) examined costs at public and private comprehensive universities in the United States. Specifically, with regard to the impact of location on costs, Sav found evidence that comprehensive institutions have regional differences in the cost structure. These differences were based also on institutional control – specifically, public comprehensive universities in the Central West spent more to produce higher education than in other regions. Private comprehensive universities in the Southeast, Great Lakes, and Far West regions have higher cost structures than those in the North East – which includes the New England and Mid East regions (Sav, 2004). However, again, the study did not consider budget models.

## **Summary of Scholarship on Higher Education Costs**

Higher education researchers and economists have produced a vast body of scholarship on higher education costs. Indeed, scholars have theorized about, and empirically investigated several inquiries regarding cost escalation and determinants of cost in higher education. Generally, these theoretical and empirical investigations have provided insight to at least three questions: (1) why do higher education costs rise faster than costs in other industries; (2) to what extent are colleges and universities cost efficient; and (3) what is the relationship between revenues and costs across higher education institutions? As a result, scholars have illuminated many implications for policy, practice, and future research. Specifically, empirical research has identified cost variations across higher education; in doing so, scholarship has shown that colleges and universities could benefit from better understanding their institutional characteristics and activities.

Although this large body of scholarship has been insightful, researchers have mostly investigated higher education costs broadly over time – specifically, most studies have used large sample sizes with hundreds of colleges and universities to investigate costs. However, researchers have not specifically investigated costs in small-sample studies to explore how colleges and universities have responded to cost escalation in higher education via new policies or practices, such as RCM. Several scholars (Cheslock, 2016; Titus et al., 2017; Toutkoushian, 1999) have noted that an investigation into decentralized budget models, such as RCM, is warranted, given RCM’s perceived positive implications on higher education costs. This study fills this deficit in knowledge. A further discussion regarding the research gaps is below.

## **Gaps and Limitations of Prior Research**

This section identifies and discusses the gaps and methodological limitations in the extant literature on RCM and higher education costs. Overall, the limitations focus on the need for more quantitative methods to explore RCM. Additionally, the limitations in the cost literature suggest the use of more context-specific studies to investigate costs.

### **Summary of the Research Gap**

Perhaps the most glaring omission from the literature is an investigation of RCM's impact on costs. Until this dissertation's study, researchers had not considered RCM with regard to its effect on costs at colleges and universities that have implemented it, despite several college administrators noting that one of their primary reasons for adopting RCM was to control costs at their institutions (Deering & Sá, 2014; Jaquette et al., 2018).

### **Methodological Limitations in the RCM Literature**

In addition to the research gap regarding RCM's impact on costs, the RCM literature has methodological limitations worth noting. First, the majority of RCM studies utilize a single-institution case study research design (Cekic, 2010; Courant & Knepp, 2002; Gros Louis & Thompson, 2002; Lang, 2002; Hearn et al., 2006; McBride et al., 2000). While this approach has proven useful for researchers to examine and understand the contextual factors, organizational factors, as well as the stakeholders that have been affected by RCM, the use of single-institution case studies has limited our general knowledge of the budget model. Specifically, the research findings from these empirical studies are institution-specific (i.e., not generalizable). Moreover, because multiple scholars have employed single-case study designs (Courant & Knepp, 2002; Gros Louis

& Thompson, 2002; Lang, 2002; Hearn et al., 2006), only two general findings have emerged: RCM has been adopted primarily to generate revenue and control costs. Institutions have realized positive and negative experiences with RCM thus far, as noted by Lang (2002) and Hearn et al. (2006). Other findings from single-institution case studies have been unconnected and disparate, thus not providing researchers, policymakers, and college administrators with a holistic view of RCM's general effects.

The use of multi-institution studies, however, has improved the quality of research on RCM. For example, Deering & Sá (2014, 2018) and Jaquette et al. (2018) were able to draw similarities and distinctions between the colleges and universities in their respective studies on RCM. However, the findings from these studies are also not generalizable – although they have provided more general insight than the single-institution case studies.

The second limitation of research on RCM is the use of qualitative methods to describe the quantitative effects of RCM. For example, in a previously discussed qualitative case study on the University of Toronto-Scarborough's (UTS) experience with RCM, Lang (2002) noted that UTS had accumulated a \$5.5 million debt two years after RCM had been fully implemented. However, the scholar did not conduct a quantitative or quasi-experimental analysis to attribute the \$5.5 million debt to RCM. Deering and Sá (2014), in a multiple-case study, revealed that three Canadian institutions implemented RCM in response to dwindling government support to colleges and universities – that is, RCM was adopted to help these institutions generate additional revenue and reduce costs. While the study revealed perceptions that RCM was useful to achieve the financial goals,

the study would have been strengthened if the authors analyzed the extent to which RCM affected revenue and costs at the institutions in the study.

The scholarship on RCM is again limited because several researchers have not applied appropriate quantitative techniques to reveal RCM's impact on quantifiable outcomes (e.g., enrollment). For example, in a study of RCM at the University of Minnesota-Twin Cities (UMTC), Hearn et al. (2006) utilized qualitative and quantitative techniques. The qualitative technique (i.e., the use of interviews) appropriately addressed their objective to capture and analyze deans' perceptions of RCM. However, the use of descriptive analysis was inadequate to investigate the extent to which RCM impacted student enrollment and the number of credit hours taught across the colleges at UMTC. Specifically, the researchers did not employ a causal or quasi-experimental research design to appropriately attribute RCM to the changes in enrollment and credit hours taught. Additionally, McBride et al. (2000), in a study on RCM at the School of Nursing at IUPUI, suggested that RCM impacted how faculty spent their time. However, the researchers also did not employ an appropriate technique to show if (or to what extent) their results might have been changed in the absence of RCM. Specifically, the descriptive methods employed by the researchers did not causally link RCM to the changes in how faculty reportedly spent their time.

Rutherford and Rabovsky's (2017) examination of RCM utilized a quasi-experimental method; however, this study, too, is limited methodologically. Specifically, Rutherford and Rabovsky (2017) employed a two-way fixed-effects linear regression model to analyze RCM's impact on two non-financial but quantitative outcomes: graduation rates and degree production. The authors found evidence that RCM positively

impacted graduation rates compared to institutions that had not adopted RCM (Rutherford & Rabovsky, 2017). However, the authors did not find evidence to show a significant difference in degree production between RCM institutions and non-RCM institutions.

However, Rutherford and Rabovsky (2017) did not take into account the various RCM structures that exist across institutions. Specifically, the scholars used a dichotomous variable to indicate which institutions used RCM and which did not. As a consequence, they were unable to capture the additional variation between institutions with regard to how they operate RCM (i.e., funding formulas, revenue and cost allocation rules, length of time since adopting RCM, etc.). Moreover, the scholars' use of linear regression analysis was limited because it could not account for the various years in which the institutions adopted RCM. Specifically, they used a two-way fixed-effects linear regression model with fixed effects on the institutions and on the years in which institutions adopted RCM. As a consequence, the analytic technique would not be able to account for institutions that may have changed their budget model from RCM to a centralized approach (or vice versa) during the sample period. This suggests that some RCM universities were perhaps not accounted for as RCM institutions, which would have biased the analysis. Lastly, and perhaps most importantly, the method used by Rutherford and Rabovsky (2017) was limited such that it could not estimate if, or to what extent, any continuous outcome (e.g., costs) may have been impacted by RCM. For example, in the context of the study, the researchers did not address whether RCM institutions would have had higher graduation rates than the non-RCM institution if RCM had not been implemented in the first place. In other words, if RCM had not been adopted by RCM

University X (i.e., any RCM university in the study), would RCM University X have had a higher graduation rate, on average, than non-RCM University Y (i.e., a non-RCM university) anyway? If this is true – that is, if RCM University X (without adopting RCM in the first place) would have realized higher graduation rates, on average, than non-RCM University Y, then it casts doubt on the study’s findings regarding RCM’s effect.

A recent empirical study attempted to overcome several methodological limitations of previous studies. Jaquette et al. (2018), in a multi-institution design, used a quasi-experimental quantitative technique called the synthetic control methodology (SCM) to assess whether RCM impacted tuition revenue at four public research universities. The SCM has been used in small-sample quantitative case studies (Abadie & Gardeazabal; Abadie et al., 2010, 2015) to compare the outcomes of a unit that has experienced an event, policy, or treatment (e.g., the adoption of RCM) to the outcomes of one or more units that did not experience the same event, policy, or treatment (i.e., the control group composed of non-RCM universities). This method will be described in greater detail in *Chapter 3: Methodology*.

The research design and analytic technique employed by Jaquette et al. (2018) addressed the limitations of previous literature on RCM. Specifically, the use of the synthetic control method enabled the researchers to (1) examine RCM within multiple cases; (2) provide context regarding each institution’s motivation for adopting RCM; and (3) analyze RCM’s impact on a quantitative measure (i.e., tuition revenue). The use of the synthetic control method addressed the need for more quantitative research on RCM. Additionally, the use of SCM allowed Jaquette et al. (2018) to overcome several limitations of the study by Rutherford and Rabovsky (2017). For example, Jaquette et al.



(2018) were able to account for variation across institutions – specifically, SCM accounted for the different years in which RCM was adopted and the different ways in which institutions operated RCM (i.e., funding formulas, allocation rules, etc.). As indicated above, Rutherford and Rabovsky (2017) were not able to account for this difference using a binary variable in their linear regression model. Additionally, the SCM analysis allowed Jaquette et al. (2018) to construct a viable control group to estimate and compare the use of RCM with what would have occurred at the institutions in the study if RCM had not been implemented. This specifically allowed the researchers to isolate RCM’s effect on tuition revenue.

The results associated with the SCM strategy used by Jaquette et al. (2018), while not generalizable, have provided significant insight regarding RCM across multiple cases. This dissertation adopted the same strategy in an investigation of RCM’s impact on costs. (Further discussion regarding how this study implemented SCM is in *Chapter 3: Methodology*.)

### **Methodological Limitations in Higher Education Cost Literature**

The literature on higher education cost, albeit vast, is limited methodologically because researchers have mostly conducted large-sample quantitative studies while neglecting the impact of institutional context on cost. Specifically, scholars have been limited in their ability to provide institution-specific context and implications for policy and practice. For example, several studies have examined cost across at least 50, and upwards of nearly 3,000 institutions (e.g., Agasisti & Salerno, 2007; Brinkman, 1981; Brinkman et al., 1986; Cohn et al., 1989; deGroot et al., 1991; Doyle, 2010; Johnes & Schwarzenberger, 2011; Koshal & Koshal, 1999; Koshal et al., 2001; Kuo & Ho, 2007;

Laband & Lentz, 2003; Mamun, 2012; Robst, 2001; Sav, 2004; Titus et al., 2017; Toutkoushian, 1999). Moreover, scholars have not been able to assess how, and to what extent institutions may have responded to issues related to cost escalation. As a consequence, several potential lessons learned from institution-specific cost structures have been, perhaps, missed. Instead, many of the implications for policy and practice that have been gleaned from the empirical literature have been far-reaching but general at best. Additionally, because there is so much variability within college and university cost structures, a more balanced research approach is warranted.

For example, some scholars have focused on specific institution types to study costs and uncover policy-relevant recommendations. More specifically, deGroot et al. (1991) examined costs at research universities, Koshal et al. (2001) studied costs at Bible Colleges, and Titus et al. (2017) investigated cost efficiency across public master's institutions. Only one study has examined costs at a single institution (Nelson & Hevert, 1992). Specifically, Nelson and Hevert (1992) explored economies of scale and scope at the University of Delaware using data from 31 departments across five years. The authors documented the importance of class size with regard to costs, among other findings previously discussed above. However, the scholars missed an opportunity to provide institution-specific context regarding the University of Delaware – specifically why they chose to study it and to what extent the findings might have practical and policy implications.

### **The Dearth of Theoretical Perspectives on RCM**

In addition to the methodological limitations of prior research, the extant academic literature on RCM is atheoretical. Only two studies (Cekic, 2010; Jaquette et

al., 2018) have been theoretically grounded. Cekic (2010) used Bolman and Deal's (2003) four frames of organizational culture (i.e., structural/rational, human resources, political, and symbolic) to elucidate how faculty and administrators perceived of the RCM budgeting and planning processes. Cekic found that perceptions among faculty and administrators had changed with regard to budgeting after RCM had been implemented. Specifically, after the institution replaced the incremental budgeting model with RCM, faculty, and administrators indicated that budgeting became less of a political/competitive process and instead became more structured. The author suggested that the RCM funding formulas and allocation rules perhaps allowed more transparency and structure in resource allocation decisions (Cekic, 2010).

Jaquette et. al (2018) used principal-agent theory (PAT) to illustrate the principal-agent relationship between central administration (i.e., the principal) and deans (i.e., the agents) within institutions that operate RCM. The authors argued that RCM provided the framework and incentives necessary to align the goals of the principals with the goals of the agents (i.e., to minimize shirking as described above). Specifically, the researchers suggested that central administrators were driven to increase tuition revenue as a result of declining state funding; and deans, through the use of RCM funding formulas and resource allocation rules, were given the incentives necessary (i.e., the ability to generate more revenue at the college-level through enrollment; and the ability to carryover unused funds year over year) to align their goals with those of central administration. The researchers hypothesized that the use of RCM would impact tuition revenue under the principal-agent relationship, and found that three of the four institutions in the study had

significantly increased the amount of tuition revenue after RCM had been implemented (Jaquette et al., 2018).

Although the application of PAT and Bolman and Deal's (2003) frameworks have proven useful, more theoretical perspectives are necessary to guide future research on RCM. This study addresses this limitation. A discussion of how this study incorporated theory is below.

### **Addressing the Gaps and Limitations of Prior Research**

This section describes how this dissertation study overcame a series of limitations from previous literature on RCM. Specifically, this study addressed the following: (1) the gap in knowledge regarding RCM's impact on institutional costs; (2) the limited use of theoretical perspectives in the RCM literature; and (3) the methodological limitations of previous studies on RCM and higher education costs.

### **Theoretical Framework**

This study is guided by two theoretical frameworks: Principal-Agent Theory and Bowen's (1980) Revenue Theory of Cost (RTC). PAT is used to theoretically frame the principal-agent relationship between central administration (i.e., the principal) and deans (i.e., the agents) at two public research universities that adopted RCM – consistent with previous research by Jaquette et al. (2018). However, this study, unlike Jaquette et al. (2018), attempts to illustrate that PAT is an appropriate framework to explain the relationship between central administration and deans with regard to RCM's impact on cost.

RTC is utilized to theoretically frame the impact of revenues on costs. Specifically, this study incorporates variables on college and university revenue sources because RTC suggests that colleges and universities raise revenue and spend it all (i.e., revenues impact costs). Many scholars (e.g., Brinkman, 1990; Clotfelter, 1996; Martin, 2011; Winston, 1999) including Bowen (1980) have argued that colleges and universities are not cost minimizers, and have instead suggested that colleges and universities seek to maximize their prestige and influence. Therefore, these scholars contend that colleges and universities, as a consequence of maximizing their prestige and influence, increase costs substantially. However, because RCM provides incentives for cost minimization – that is, deans are allowed to carryover unexpended revenue and are required to carryover budget deficits from year to year – this study seeks to uncover if, and to what extent, RCM might impact costs. Further discussion regarding the use of these theoretical perspectives is below.

### **Principal-Agent Theory**

As described in the above section on theoretical perspectives in the higher education cost literature, PAT has been used by economists, political scientists, and higher education researchers to explain the contractual relationship between two or more entities (Cheslock et al., 2016; Jaquette et al., 2018; Lane & Kivisto, 2008; Martin, 2011; Tandberg et al., 2017; Titus, 2009). Specifically, PAT posits that a *principal* contracts the services of one or multiple *agents* to perform duties in which the *principal* does not have the time, knowledge, skill, or desire to perform him/her/itself (Lane & Kivisto, 2008). According to PAT, principal-agent relationships will possess misaligned goals, such that the goals of the *principal* may differ in part or in whole from the goals of the *agent*

(Kivisto, 2005, 2007; Lane & Kivisto, 2008). As a consequence, PAT suggests that agents will shirk by working towards their own self-interests versus the interests of the principal. Thus, PAT recommends that principals develop incentives to mitigate shirking to ensure the achievement of the principals' goals (Lane & Kivisto, 2008).

Applied to higher education, scholars have used PAT to model several different principal-agent relationships. For example, Titus (2009) used PAT to illustrate the principal-agent relationship between states and their respective public higher education institutions. He argued that the goal of states (i.e. the principals) with regard to higher education was to produce bachelor's degrees. Moreover, the contract used by states to produce bachelor's degrees was in the form of higher education appropriations to public colleges and universities. Titus (2009) revealed a positive significant relationship between state spending on higher education and the production of bachelor's degrees and concluded that PAT was an appropriate framework from which to study the relationship between states and public higher education institutions.

Tandberg et al. (2017) employed PAT to theoretically frame the relationship between governors (i.e., the principal) and state higher education executive officers (SHEEOs) – the agents. The researchers specifically sought to investigate how the relationship between governors and SHEEOs might influence higher education funding. The goal of the principal in this study was to influence funding to higher education. However, because there is variation across states, the authors suggested that the contract between governors and SHEEOs with regard to higher education funding was predicated on the authority that governors possessed over SHEEOs. Specifically, the authors hypothesized that if a governor had the authority to hire and fire a SHEEO, then it would

result in lower state spending on higher education. However, if the SHEEO was independent of the governor's authority (i.e., appointed by the legislature) then it would result in higher state spending on higher education. Tandberg et al. (2017) found that state funding was lower, on average, when governors maintained strong authority over SHEEOs. The scholars also concluded that PAT was an effective conceptual lens through which to examine the governor's influence over higher education.

Finally, Jaquette et al. (2018) utilized PAT to frame the relationship between central administration (i.e., the principal) and the deans (i.e., the agents) in a study on RCM. The researchers argued that the goal of central administrators was to increase tuition revenue. Moreover, the authors argued that the RCM funding formulas served as the contract to incentivize deans to grow enrollment as a mechanism to increase tuition revenue. Specifically, through the devolution of budget authority to the deans, the authors argued that RCM incentivized deans by permitting the carryover of revenue surpluses from year to year. This, in turn, created goal alignment between central administrators and deans with regard to revenue growth. The scholars revealed that tuition revenue had significantly increased at three of the four universities in the study. Additionally, the scholars validated the use of PAT to explain the relationship between central administrators and deans (Jaquette et al., 2018).

These studies (Jaquette et al., 2018; Robossi, 2017; Tandberg et al., 2017; Titus, 2009) have explicitly and implicitly revealed three elements to identify when applying PAT as a theoretical perspective: (1) the principal-agent relationship; (2) the goal of the principal; and (3) the contract or mechanism used to bind the work of the agents to the goals of the principal.

In the context of this dissertation study, PAT is used to theoretically frame the principal-agent relationship between central administration and deans (i.e., the leaders of academic responsibility centers) at two public research universities that have adopted RCM. Specifically, I argue that under RCM, the goal of principals (i.e., central administration), in addition to increasing revenue (as has been explored by scholars), is also to minimize costs (Deering & Sá, 2014; Jaquette et al., 2018). This notion suggests that RCM is implicitly guided by the economic theory of the firm which contends that for-profit firms seek to maximize profit (i.e., maximize revenues and minimize costs). However, because most higher education institutions are non-profit organizations, the notion of cost minimization that implicitly guides RCM, is contrary to how scholars (Brinkman, 1990; Clotfelter, 1996; Martin, 2011; Winston, 1999) have described the behavior of colleges and universities. However, using PAT as a guide, I argue that the use of RCM serves as the contract that binds the principal-agent relationship of central administration and deans to guide cost minimization. Specifically, under RCM, deans possess the financial authority to make revenue and cost-related decisions. Deans are disincentivized to allow their college's expenditures to exceed revenues because RCM requires deans to carry over budget deficits from year to year. Multiple years of budget deficits may not be well received by the central administration, thus further disincentivizing deans to overspend. In the context of PAT, the use of disincentives under RCM may mitigate *shirking* among deans and allow the academic units (and university by extension) to minimize costs.



## **Revenue Theory of Cost**

Bowen's (1980) Revenue Theory of Cost (RTC) is also used to guide this study. As discussed previously, RTC posits that colleges and universities function with the goal of maximizing their prestige, excellence, and influence. To carry out their goals with regard to prestige maximization, RTC suggests that institutions of higher education raise as much money as they can and then spend all of the money they raise (Bowen, 1980). Moreover, because there is no discernable way to identify when an institution has maximized its prestige, excellence, or influence, Bowen (1980) further posits that spending is incessant. This further suggests two notions: (a) not-for-profit colleges and universities are not cost minimizers; and (b) cost escalation in higher education institutions is the result of institutional choice.

As noted in a previous section of this study, higher education scholars have used RTC to guide inquiry into studies on higher education costs (Archibald & Feldman, 2008; Martin & Hill, 2014; Leslie et al., 2012). Archibald and Feldman (2008) tested cost disease theory with RTC to elucidate which theory better described cost escalation in higher education. The scholars found more evidence to support cost disease theory, arguing that higher education costs have risen mostly as a result of external market pressures from other industries versus internal choices made by higher education institutions (Archibald & Feldman, 2008). Martin and Hill (2014) found the opposite conclusion in a study that also tested cost disease and RTC. Leslie et al. (2012) found evidence that revenues impact costs differently across public and private universities. Specifically, with regard to RTC, Leslie et al. (2012) revealed that private universities expended resources in a prestige-maximizing manner – specifically, private institutions

allocated larger shares of their revenue for scholarships and research compared to public institutions (Leslie et al., 2012).

Although the scholars did not reveal that public universities expended revenues in a prestige-maximizing manner, Leslie et al. (2012) did show that revenues impacted costs at public universities. For example, Leslie et al. (2012) found that for each dollar increase in tuition revenue received by public institutions, they spent almost 46 cents on instruction and 11 cents on scholarships.

Based on the evidence that revenues impact costs, RTC is utilized in the context of this study to theoretically frame the impact of revenues on costs. Specifically, this study incorporates variables on college and university revenue sources because RTC suggests that colleges and universities raise revenue and spend it all (i.e., revenues impact costs).

### **Addressing the Methodological Limitations of Previous Research**

This study overcomes several methodological limitations of previous research by employing a research design that addresses the challenges outlined in the *Gaps and Limitations* section above. On one hand, previous literature on RCM is heavily composed of single-institution case studies. As a consequence, our knowledge of RCM has been limited and highly context specific. On the other hand, previous scholarship on higher education cost is heavily quantitative, with the majority of studies examining costs across hundreds, and sometimes thousands, of colleges and universities. As a result, no known research has explored costs in a small-sample and contextualized manner. Specifically,

researchers have not investigated costs across a small sample of colleges and universities using a quantitative technique while also providing context on the institutions.

This study utilizes the synthetic control method (SCM) to address the research question and limitations of previous literature (Abadie et al., 2010). Specifically, SCM is a quantitative method developed in economics to estimate the causal effects of policy, idiosyncratic events, or interventions. SCM is used in single-case or multiple-case studies to estimate the treatment effects of some policy, event, or intervention by comparing the outcomes of each case to the estimated outcomes of a synthetic version of each case. (A thorough discussion of SCM will be described in *Chapter 3: Methodology*.) Specifically, this study explores the effect of RCM on total operating costs at the University of New Hampshire (UNH) and the University of Arizona (UofA). These universities were selected for several reasons: (1) the leaders of each of these institutions cited (among others) that their motivation to implement RCM was to incentivize cost minimization across their respective institutions; (2) there was adequate public data available with regard to how both UNH and UofA operate their RCM models unlike other institutions that use RCM; (3) as illustrated in Table A2, each of these universities has different levels of experience with RCM – specifically, UNH adopted RCM in the year 2000 and UofA adopted RCM in 2015; (4) each university implements RCM differently – that is, they employ different funding formulas and allocation rules; and (5) the synthetic control method (the method used in this study) allows the researcher to assess the treatment effects of one unit (i.e., university) at a time.

## **University of New Hampshire**

Founded in 1866, the University of New Hampshire (UNH) is a public research university located in Durham, New Hampshire. UNH is the state flagship institution and currently enrolls over 13,000 undergraduates and over 2,000 graduate students across 13 colleges and schools (UNH Facts and Figures, 2019). Additionally, UNH manages an operating budget of nearly \$600 million and offers associate's degrees, baccalaureate degrees, and graduate degrees across 200 academic programs. UNH boasts an 18:1 student-faculty ratio (UNH Facts and Figures, 2019).

*Motivations for Adopting RCM.* UNH implemented RCM on July 1, 2000, after an 18-month RCM exploration study was conducted at the request of the then university president Joan Leitzel. President Leitzel cited five reasons for moving the campus to RCM. Among them she noted “[t]here will be stronger incentives for cost effectiveness and revenue generation” (Joan Leitzel, personal communication, January 14, 2000) because the university had experienced significant changes in enrollment, total operating costs, and total revenue prior to the implementation of RCM.

Leading up to the implementation of RCM at UNH, members of the RCM steering committee, including the then provost and vice president for finance and administration wrote articles (Corvey, 1999; Hiley, 1999) to the campus community explaining the implementation process and providing insight regarding their intentions and rationale for adopting RCM. The tenor and focus of these articles centered on key motivations for adopting RCM that were in large part around the desire for cost control and to grow revenue. For example, in describing decision-making under UNH's centralized budget model, the then provost David Hiley noted “[i]t is insufficiently

flexible, often too removed from where the action is in the institution and offers too few incentives for cost control and revenue enhancement” (Hiley, 1999, para. 3). Candace Corvey, the then vice president of finance and administration, wrote that “[t]he risk of not moving to RCM is that we will retard institutional evolution and progress, because we will not be as facile, cost-effective, entrepreneurial or forward-thinking as possible” (Corvey, 1999, para. 4).

***Student Enrollment and Financial Context Prior to RCM.*** As noted above, UNH experienced changes in enrollment, operating costs, and revenue prior to the implementation of RCM. For example, between 1980 (the earliest year for which data are available) to 1999 (the year prior to the implementation of RCM) the number of undergraduate students increased by only six percent, but the number of graduate students increased by 86%. As suggested by previous research on higher education costs, the cost of graduate education, on average, is higher than undergraduate education. Thus, the significant increase in graduate students between 1980 and 1999 may have influenced cost increases at UNH.

Indeed, between 1980 and 1999, total operating costs increased by 71% (after adjusting for inflation in 1999 dollars). In 1999, the total expenditures at UNH were approximately \$300 million, and instructional costs represented about 24% of total expenditures, auxiliary enterprises accounted for 20%, and research expenditure represented about 18% of total expenditures. Academic support, student services, and institutional support represented six, three, and six percent of total revenue, respectively in 1999.

Total revenue, on the other hand, increased by 74% between 1980 and 1999. Tuition and fee revenue represented the largest source of revenue; it increased from 28% of total revenue in 1980 to 34% in 1999. Consistent with other public institutions during this time period, state appropriations as a percentage of total revenue declined from 22% in 1980 to 16% in 1999. Thus, the leaders of UNH sought to generate additional revenue and control costs as the institution became more reliant on tuition revenue versus public funding.

*Reviews and Evaluations of RCM at UNH.* Since RCM was implemented in 2000, UNH has formally reviewed its RCM model internally three times: in 2006, 2009, and 2015. However, none of the internal reviews have explicitly examined the extent to which RCM impacted cost control at UNH. More specifically, the scope of each of the internal reviews differs based on the level of priority at the time of the review. For example, the 2006 review sought to “analyze the extent to which UNH has or has not achieved greater efficiency and effectiveness in curriculum, research/outreach, and administration under RCM” (UNH, 2006, para. 4). However, the only major finding from the 2006 review suggested that RCM had not harmed the academic quality of programs at UNH. The review committee did not provide any evidence to show if UNH controlled or reduced costs after RCM had been implemented.

Similarly, the 2009 review did not reveal evidence to show that the institution had become more cost efficient since the implementation of RCM (UNH, 2009). Although, several changes were made to UNH’s RCM model as a result of the 2009 review including (a) how the RCM allocation rules funded central administrators, moving from a general assessment to a percentage share of revenues between the central administration

and responsibility centers; (b) the adjustment of how overhead revenues are allocated from grant funds received (i.e., facilities and administration) – specifically, UNH removed the vice president for research out of the allocation; and (c) UNH began using state appropriations to fund a portion of financial aid for New Hampshire resident students (UNH RCM Operating Manual, 2017).

In the most recent review (i.e., the 2015 review) the budget committee surveyed the campus community on several issues related to the UNH’s budget model and how it was working. Nearly one-third of the respondents reported “no understanding” of RCM; two-thirds indicated that they do not believe that RCM encourages innovation and revenue growth; and nearly 61% reported that they did not believe that RCM encourages efficiency and effectiveness (UNH, 2015, p. 7). However, because RCM was implemented, in part, to address escalating costs at UNH, and because the internal reviews of RCM did not consider costs in their analysis, this study seeks to elucidate RCM’s effect on total operating costs.

### **University of Arizona**

Located in Tucson, Arizona, the University of Arizona (UofA) was established in 1885 and serves as the state of Arizona’s flagship university. UofA is a public research university that enrolls over 45,000 undergraduate and graduate students across 40 colleges and schools, including two hospitals (University of Arizona, 2019). In 2018, the campus managed a nearly \$2.4 billion operating budget (University of Arizona, 2019).

*Student Enrollment and Financial Context Prior to RCM.* RCM was fully operational beginning July 1, 2015. Between 2003 and 2014 (the year before RCM was

implemented), UofA experienced a 34% decline in state appropriations (after adjusting for inflation in 2014 dollars). Despite these substantial decreases in state appropriations, undergraduate enrollment increased by 16%, and graduate enrollment rose by eight percent between 2003 and 2014. Tuition revenue helped to offset the loss in state appropriations, growing by nearly 152% between this time period. Total expenses, on the other hand, rose by nearly 30% between 2003 and 2014 – pacing at nearly the same rate as revenue growth during this period. This changing financial picture at UofA prompted administrators to consider adopting RCM in 2015.

***Motivations for Adopting RCM and RCM Timeline.*** Consistent with all RCM adoptions, the adoption of RCM at the UofA came at the request of the university president – then president Ann Hart. President Hart convened a steering committee to investigate the feasibility of implementing RCM in 2012 (University of Arizona, 2017, 2019). The steering committee was composed mostly of faculty and administrators from all areas of the campus, and even included one student leader. The steering committee was further divided into nine sub-committees for various aspects of RCM – ranging from the subcommittee on undergraduate tuition to the subcommittee on facilities and space (University of Arizona, 2017, 2019). Between fall 2012 and fall 2013, the steering committee met to develop the guiding principles for RCM and identify key personnel and campus units to ensure RCM’s success (University of Arizona, 2019). By the spring of 2014, the UofA began testing components of RCM on a small scale and by the fall of 2014, UofA operated concurrent budgets – one using the old system and the other using a prototype of RCM. After testing had been completed, the steering committee formally



recommended to the president of UofA that RCM be fully implemented beginning July 2015.

Two of the three motivating factors listed in UofA's RCM implementation website illustrate the institution's desire to increase transparency around revenues and costs, and the desire to grow revenue while also becoming more cost effective in the wake of significant financial changes at the university. The UofA conducted a three-year internal review of RCM in 2018 but no report has been furnished publicly. As a consequence, we cannot discern whether, or to what extent the reviewers considered RCM's impact on costs at UofA. This study investigates if and to what extent RCM impacted operating costs at the UofA.

### **Chapter Summary**

This chapter highlighted how scholars have considered RCM and higher education costs in the extant literature. Notable among the many lessons revealed throughout the RCM and higher education cost literature is that academics have not yet considered a study on RCM in relation to costs. Moreover, the lack of theoretical perspectives and quantitative research on RCM has limited the field's knowledge of RCM's impact broadly. This chapter describes how this dissertation study approached RCM with regard to its impact on costs at two public research universities. *Chapter 3: Methodology* further describes how this study examines the influence of RCM on cost using the synthetic control methodology.

## **Chapter 3: Methodology**

### **Introduction**

The purpose of this study is to examine the effect of RCM on total operating costs at two public research universities in the United States. Specifically, this study uncovers the extent to which RCM as a budget model and management tool impacted operating costs at the University of New Hampshire and the University of Arizona. This study is guided by the following research question: *What is the impact of RCM on total operating costs at two public research universities in the United States?*

The synthetic control method (SCM) is employed to address the research question. For clarity and ease of understanding, I first describe SCM conceptually, followed by a mathematical illustration of its key components. Next, I discuss how SCM is an appropriate method for addressing the research question relative to other methods. Thereafter, I describe how in this study, I employed the SCM to address the research question. This includes a discussion of the pertinent data, variables, sample periods, and the procedures I underwent to generate results. I then conclude this chapter with some limitations of the SCM.

### **Research Design**

#### **Overview of Synthetic Control Methodology**

The SCM is a quantitative, data-driven method developed in economics to estimate the causal effects of policies, programs, idiosyncratic events (e.g., natural disasters, terrorism, etc.), or interventions (Abadie & Gardeazabal, 2003; Abadie, Diamond, & Hainmueller, 2010, 2015). SCM has been employed by scholars mostly in

economics but also in other fields such as public health, criminal justice, and higher education (Becker & Klobner, 2016; Krief, Grieve, Hangartner, Turner, Nikolova, & Sutton, 2016; Liu, 2015). For example, in economics, Abadie and Gardeazabal (2003) employed SCM to estimate the economic effects of terrorism in the Basque Country. Becker and Klobner (2016) used SCM to approximate the Mafia's impact on per capita Gross Domestic Product (GDP) in Italy. Similarly, Adhikari, Duval, Hu, and Loungani (2018) employed SCM to reveal the effect of economic reforms on per capita GDP in New Zealand, Australia, The Netherlands, Denmark, Ireland, and Germany. Additionally, in a study estimating the effect of tourism taxation on tourism demand in Villasimius. Biagi, Brandano, and Pulina (2016) used SCM. Abadie et al. (2010) investigated the extent to which California's Proposition 99 affected tobacco cessation using SCM. Additionally, SCM was employed by Abadie et al. (2015) to estimate the effect of the 1990 German reunification on per capita GDP in West Germany. Barone and Mocetti (2014) used SCM to investigate the impact of natural disasters on per capita GDP in two Italian regions.

At least one study from public health (i.e., Krief, Grieve, Hangartner, Turner, Nikolova, & Sutton, 2016) used SCM. Specifically, Krief et al (2016) used SCM to evaluate the impact of a pay-for-performance initiative on health outcomes at hospitals that implemented the initiative. Likewise, at least one criminal justice study (Rydberg, McGarrell, Noris, & Circo, 2018) has utilized SCM – specifically to evaluate the impact of a place-based police patrol intervention on violent crimes in Flint, Michigan.

Applied to higher education, researchers (Bonander, Jakobsson, Podesta, Svensson, 2016; Hinrichs, 2012; Liu, 2015; Jaquette et al., 2018) have employed SCM in

at least four studies. For example, Hinrichs (2012) used SCM to examine the extent to which California’s ban on affirmative action in college admissions impacted enrollment at the University of California (UC) campuses. Liu (2015) employed SCM to investigate the effects of the Morrill Act of 1862 (i.e., the land-grant program) on local economies between 1860 and 1940. Specifically, Liu (2015) examined the extent to which universities who received land-grant designation (as a result of the Morrill Act) impacted the population density of counties where the institutions are located. In a similar study, Bonander et al. (2016) used SCM to estimate the effects of two Swedish universities that were granted university rights in 1999 on regional per capita GDP. Finally, Jaquette et al. (2018) employed SCM to examine the effect of RCM on tuition revenue at four public research universities in the United States.

To describe SCM’s procedure, utility, and appropriateness for a study on RCM, a simple illustration that depicts the pre-treatment and post-treatment concepts underlying SCM is provided in Figure A1. Thereafter, the mathematical representation of SCM is discussed.

### **SCM Procedure**

The synthetic control method aims to estimate treatment effects through a data-driven statistical process known as the root mean square prediction error (RMSPE). The purpose of the RMSPE is twofold: (a) to first construct the synthetic control unit (defined below); and (b) to use the synthetic control unit to estimate the post-treatment counterfactual (defined below).

The synthetic control unit is an estimation of the control group (i.e., a group of “comparable” comparison units that did not receive the treatment). As illustrated in

Figure A1, the purpose of the synthetic control unit (i.e., the dotted blue line) varies between the pretreatment period of the study (i.e., the period before the treatment occurred), and the post-treatment period of the study (i.e., the period after the treatment occurred).

In the pretreatment period, the synthetic control unit is approximated using a set of predictor variables (described below) to statistically resemble the treated unit (i.e., possess nearly identical characteristics, statistically speaking). The characteristics for colleges and universities could be: enrollment, the number of academic programs, the number of faculty and staff, and the operating budget, to name a few. In the pretreatment period, the SCM minimizes the distance (i.e., differences) between the synthetic control unit and the treated unit (i.e., the dotted blue line and the solid red line shown in Figure A1). The extent to which the treated unit and the synthetic control unit resemble one another impacts the estimation of the counterfactual (defined below).

In the post-treatment period of the study, the purpose of the synthetic control unit is to estimate the post-treatment *counterfactual* using the RMSPE. The counterfactual is defined as the post-treatment outcome of the treated unit in the absence of the treatment (Krief et al., 2016). This is also illustrated in Figure A1. The post-treatment counterfactual is used to assess treatment effects (if any) by subtracting the post-treatment outcome of the treated unit (i.e., the solid red line after the treatment year in Figure A1) from the post-treatment outcome of the counterfactual (i.e., the dotted blue line after the treatment year in Figure A1). Treatment effects are assessed at each interval in the post-treatment period. Therefore, as illustrated in Figure A1, treatment effects

would be assessed for 2003, 2004, and 2005. (Further discussion on these concepts is below.)

### **Estimating a Synthetic Control Unit**

As described above, the purpose of the synthetic control unit varies between the pretreatment period of the study (i.e., the period before the treatment occurred) and the post-treatment period of the study (i.e., the period after the treatment occurred). In the pretreatment period, the purpose of the synthetic control unit is to statistically resemble the treated unit. Two elements are required to estimate a synthetic control unit in the pretreatment period: (1) a *donor pool* of “comparable” untreated units from which to statistically resemble the treated unit; and (2) *predictor variables* gleaned from theory or prior research that impact (or are related to) the *outcome* variable.

***Donor Pool.*** The donor pool (i.e., the group of “comparable” untreated units) is used to create a synthetic control unit that best resembles the treated unit during the pretreatment period. As suggested by Abadie et al. (2015):

[it is important to restrict the donor pool] to units with outcomes that are thought to be driven by the same structural process as for the unit representing the case of interest and that are not subject to structural shocks to the outcome variable during the sample period of the study (p. 497).

This means that researchers should develop a donor pool that includes untreated units that are “comparable” to the treated unit.

***Predictor variables.*** After the donor pool is selected, the SCM estimates a synthetic control unit (in the pretreatment period) using predictor variables (also called covariates) to predict the outcome variable under consideration (i.e., the dependent variable) (Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015). The predictor

variables are selected by the researcher and can come from theory and prior research on the outcome variable of interest (i.e., the dependent variable). The SCM procedure generates weights for each of the untreated units from the donor pool (based on the extent to which the predictor variables of the untreated units resemble the predictor variables of the treated unit). The SCM also assigns weights to each of the predictor variables (based on the extent to which the predictor variables explain the outcome variable). In both cases, the SCM assigns weights that range from zero to one and sum to one (Abadie et al., 2010, 2015). For example, untreated units from the donor pool with predictor variables that have weights closer to one possess more predictive power (and more closely resemble the treated unit in the pretreatment period) than untreated units with predictor variables that are weighted closer to zero. Likewise, predictor variables with weights closer to one have higher predictive power than those closer to zero. This procedure is done by minimizing the difference between the pretreatment characteristics of the treated unit and the pretreatment characteristics of the untreated units (i.e., the RMSPE) (Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015). Theoretically, this means that the treated unit and the synthetic control unit should possess nearly the same characteristics (i.e., *predictor and outcome variables*) in the pretreatment period.

With regard to the number and type of predictor variables, Abadie and Gardeazabal (2003) note that the SCM is not stifled by the number of predictor variables. Moreover, SCM is not hindered by predictor variables that are unrelated to the dependent variable. Specifically, the SCM would assign lower weights (or weights of zero if they are unrelated) to variables that are unrelated (i.e., do not help to predict) the outcome variable (Abadie & Gardeazabal, 2003). This is one of the many benefits of SCM over

traditional regression techniques that will be discussed further below. In addition, SCM allows for the inclusion of lagged (i.e., pretreatment) outcome variables as predictor variables (Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015). Including predictor variables and isolating specific years in the analysis helps to decrease the pretreatment RMSPE, which in turn, helps to increase confidence in the post-treatment counterfactual (discussed in the next section).

### **Assessing Treatment Effects**

After the synthetic control unit is generated, the SCM estimates a post-treatment counterfactual for each of the periods (e.g., years) in the post-treatment period. Specifically, the SCM approximates what would have been observed by the treated unit if the treatment had not occurred (i.e., the counterfactual). This, in turn, allows the researcher to assess the impact of a treatment (i.e., the treatment effect) after the treatment has occurred. This process is done by subtracting the outcome of the treated unit from the estimated post-treatment outcome of the synthetic control unit (Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015). A post-treatment outcome is estimated separately for each period in the post-treatment period. Thus, if there are three post-treatment periods, then there will be three estimated post-treatment outcomes.

### **Placebo Tests and Inference in SCM**

The aim of establishing causality is to minimize bias by testing alternative explanations for a treatment's effect on a given outcome. In SCM, this is done through placebo tests and sensitivity analyses. Inference under SCM is different from inference in traditional regression techniques. As noted by Abadie et al. (2015):

The use of statistical inference in comparative case studies is difficult because of the small-sample nature of the data, the absence of randomization, and the fact



that probabilistic sampling is not employed to select sample units. These limitations complicate the application of traditional approaches to statistical inference (p. 499).

However, SCM procedures account for these limitations through the use of falsification exercises called “placebo studies” (Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015). These falsification exercises are akin to permutation tests. As noted by Cavallo, Galiani, Noy, and Pantano (2010), the quality of inference resulting from the placebo tests increases with the number of donor units or the number of pretreatment periods in the study. Placebo studies (or tests) are of at least two types: in-time placebo tests and in-place placebo tests.

In-time placebo tests enable the researcher to test the time-effects of treatment by allowing the researcher to artificially change the time in which an intervention actually takes place by replacing it with a time that the intervention did not take place (Abadie et al., 2015). The purpose of the in-time placebo test is to determine the extent to which the SCM results based on an artificial change in the time an intervention might vary from the SCM results of when the intervention actually took place (i.e., the original SCM results). If the results of the in-time placebo tests reveal different results than the actual treatment effect, then confidence in the treatment effect is increased. However, if the results of the in-time placebo test are similar to the actual treatment effect, then confidence in the finding is diminished.

The in-space (across unit) placebo test allows the researcher to artificially assign the treatment to each of the untreated units that make up the donor pool. The purpose of this test is to discern the probability of obtaining a placebo effect (i.e., the treatment effect of an untreated unit) that is at least as large as the treatment effects as the main

results. Specifically, using randomization inference, the in-space placebo test allows the researcher to estimate the cumulative distribution of "placebo" effects for each post-treatment period. Thereafter, the researcher can calculate the probability of obtaining a placebo effect that is greater than or equal to the actual treatment effect for each post-treatment period. The probability of obtaining placebo effects equal to or greater than the treatment effect is illustrated using *p-values*. As noted by Abadie et al. (2015):

As in traditional statistical inference, a quantitative comparison between the distribution of placebo effects and the synthetic control estimate can be operationalized through the use of *p-values*. In this context, a *p-value* can be constructed by estimating in-space placebo effects for each unit in the sample and then calculating the fraction of such effects greater than or equal to the effect estimated for the treated unit (p. 500).

Specifically, these *p-values* represent the probability of obtaining a placebo effect at least as large as the treated unit when the treatment is arbitrarily re-assigned to all non-treated units in the dataset. *P-values* closer to zero indicate greater confidence in the treatment effect for each period. Conversely, high *p-values* (i.e., those closer to one) suggest lower confidence in the treatment effect for that period. (A mathematical calculation of *p-values* generated from the in-place placebo test is below.)

*P-values* in SCM are based on randomization inference, as noted above. Scholars who have employed SCM (Adhikari & Alms, 2016; Barone & Mocetti, 2014; Jaquette et al., 2018) determine significance based on an arbitrary threshold of the *p-value* – similar to researchers who employ regression techniques (which determine significance based on hypothesis tests and confidence intervals). Specifically, scholars who have employed SCM have considered a treatment effect to be causally significant if the estimated *p-*

$values \leq 0.10$ . This means that a causally significant treatment effect would represent at most a 10% probability of the treatment effect occurring by chance. A  $p$ -value of 10% also represents a 90% probability that the treatment effect did not occur by chance.  $P$ -values above 10% may indicate that a treatment had an impact on a given outcome, however, higher  $p$ -values include a higher probability of bias.

### **Mathematical Representation of SCM**

The notation in this section to explain SCM mathematically is adopted from Abadie et al. (2010). Suppose there are  $j + 1$  units, with  $j = 1$  serving as the treated unit (i.e., the unit that experienced the policy, event, or treatment) and  $j = 2, \dots, J + 1$  serving as the untreated units in the donor pool (as described above). Let the total number of observed pretreatment periods  $T_0$  and the number of post-treatment periods be  $T_1$  such that the total sample period is  $T = T_0 + T_1$ . Let  $\alpha_{jt}$  be the causal effect for unit  $j$  at time  $t$  and be expressed as:

$$\alpha_{jt} = Y_{jt} - Y_{jt}^* \quad (1)$$

$$Y_{jt} = Y_{jt}^* + \alpha_{jt}D_{jt} \quad (2),$$

where  $Y_{jt}$  is the *observed* outcome (i.e., the treated unit),  $Y_{jt}^*$  is the counterfactual, and  $D_{jt}$  is an indicator variable that takes the value of 1 for the treated unit after  $T_0$  and takes the value of zero otherwise. The counterfactual is an estimation of the post-treatment outcome of the treated unit in the absence of the treatment. The counterfactual  $Y_{jt}^*$  can be expressed mathematically as:

$$Y_{jt}^* = \delta_t + \theta_t Z_j + \lambda_t \mu_j + \varepsilon_{jt} \quad (3),$$

where  $\delta_t$  is a time fixed effect,  $Z_j$  is a  $(r \times 1)$  vector of time-invariant covariates (not impacted by the treatment),  $\theta_t$  is a  $(1 \times r)$  vector of time-varying coefficients,  $\lambda_t$  is a

$(1 \times F)$  vector of unobserved time-varying coefficients,  $\mu_j$  is a  $(F \times 1)$  vector of time-invariant unobserved predictor variables, and the error terms  $\varepsilon_{jt}$  are unobserved transitory shocks across units with a mean of zero (Krief et al., 2016).

To estimate the causal effect(s)  $\alpha_{1t} = \alpha_{1T_0+1}, \dots, \alpha_{1T}$  for  $t > T_0$ , the SCM first approximates a synthetic control unit that best resembles the pretreatment characteristics of the treated unit  $Y_{jt}$  and then estimates the counterfactual  $Y_{jt}^*$  for each post-treatment period, as shown in equation (1).

**Estimating a Synthetic Control Unit.** The SCM aims to estimate the unobserved  $Y_{jt}^*$  to generate a synthetic control unit that best resembles the treated unit in the pretreatment period. The synthetic control unit is estimated through a data-driven process that assigns a weight  $w_j$  to each potential synthetic control (i.e., each untreated unit in the donor pool). The synthetic control unit can be expressed as a  $(J \times 1)$  vector of weights  $W = (w_2, \dots, w_{J+1})'$  with  $0 \leq w_j \leq 1$  for  $j = 2, \dots, J + 1$  and  $w_2 + \dots + w_{J+1} = 1$ . Each weight within the vector  $W$  represents a potential synthetic control (i.e., untreated units from the donor pool) for the synthetic control unit. Specifically, the weights in  $W$  range from one to zero and sum to one. Synthetic controls with weights closer to zero have lower explanatory power compared to synthetic controls with weights closer to one. Applied to equation (3), the value of the outcome variable for each synthetic control is indexed in  $W$  and can be expressed as:

$$\sum_{j=2}^{J+1} w_j Y_{jt}^* = \delta_t + \theta_t \sum_{j=2}^{J+1} w_j Z_j + \lambda_t \sum_{j=2}^{J+1} w_j \mu_j + \sum_{j=2}^{J+1} w_j \varepsilon_{jt} \quad (4)$$

As noted by Abadie et al. (2015) and Fremeth et al. (2016), a donor pool may contain heterogeneity based on the pretreatment predictor variables used to create the synthetic control unit. However, researchers should not select synthetic controls (i.e.,

untreated units from the donor pool) to be a part of the synthetic control unit if those units do not have relatively high weights,  $W$  (Abadie et al., 2010). The data-driven process to estimate the synthetic control unit is called the root mean square prediction error (RMSPE).

In the pretreatment period, the RMSPE allows researchers to select untreated units to be a part of the synthetic control unit based on the weights generated by the calculation. Using the RMSPE, SCM chooses  $W$  to minimize the weighted difference between the treated unit and synthetic control unit based on the values of the pretreatment predictor variables of the outcome variable (i.e., the dependent variable). The RMSPE can be expressed as:

$$\sqrt{\frac{1}{T_0} \sum_{t=1}^{T_0} (Y_{1t} - \sum_{j=2}^{J+1} w_j Y_{jt}^*)^2}$$

As discussed previously, the set of predictor variables can include lagged outcome variables, as well as predictor variables in specific years. The predictor variables that have a strong relationship to the outcome variable receive higher weights in determining  $W$  compared to predictor variables that do not have strong predictive power (Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015).

The process of selecting  $W$  is based on the pretreatment predictor variables  $k$ . Let  $X_1$  be a  $(k \times 1)$  vector containing the values of the pretreatment variables for the treated unit and let  $X_0$  be a  $k \times j$  matrix containing the values of the pretreatment variables for the untreated units  $j = 2, \dots, J + 1$ .  $W$  minimizes the difference between the pretreatment variables of the treated unit  $X_1$  and the pretreatment variables of the synthetic control unit  $X_0W$ . This process can be expressed as:

$$\sum_{m=1}^k v_m (X_{1m} - X_{0m}W)^2,$$

where  $v_m$  represents the weight that reflects the predictive power of variable  $m$  on the outcome variable and  $V$  represents a non-negative, diagonal matrix whose elements sum to one. As mentioned previously, predictors with higher explanatory power have values  $v_m$  closer to one and those with minimal or no explanatory power have values  $v_m$  closer to zero.

**Assessing Treatment Effects.** After the synthetic control unit is estimated – using the appropriate untreated units (from the donor pool) whose pretreatment predictor variables closely resemble the pretreatment variables of the treated unit – researchers can then estimate the treatment effect using the post-treatment RMSPE. Specifically, the post-treatment RMSPE approximates a counterfactual for each of the post-treatment periods in the study. Treatment effects are estimated by simply taking the difference between the outcome of the treated unit from the counterfactual (i.e., the outcome of the synthetic control unit in the absence of the treatment). Therefore, to estimate the causal effect(s)  $\alpha_{1t} = \alpha_{1T_0+1}, \dots, \alpha_{1T}$  for  $t > T_0$ , mathematically, this process can be expressed as:

$$\alpha_{1t} = Y_{1t} - Y_{1t}^* = Y_{1t} - \sum_{j=2}^{J+1} w_j Y_{1t}^* \quad (5),$$

where  $Y_{1t}$  represents the outcome of the treated unit,  $w_j$  represents the weights of the synthetic controls  $j = 2, \dots, J + 1$  at time  $t$  for the counterfactual  $Y_{1t}^*$ . The treatment effect must be calculated separately for each time  $t$  of the posttreatment. Placebo tests, as described above, are conducted to test for the robustness of the findings.

**Placebo Tests and Inference.** SCM employs a series of falsification tests (similar to permutation tests) to examine the quality and robustness of the estimated treatment effects (Abadie & Gardeazabal, 2003; Abadie et al., 2010; Cavallo et al., 2010).

Specifically, the in-space (across unit) placebo test is an iterative test that arbitrarily re-assigns the treatment to each of the untreated units in the donor pool. This placebo test allows the researcher to identify whether the estimated effect of the actual treatment is large relative to the cumulative distribution of the estimated “treatment” effects of the untreated units (i.e., placebo effects).

*P-values* in SCM are probabilities based on the extent to which the distribution of placebo effects reveals more effects that are larger than the actual treatment effect. Using the in-space placebo test as an example, Galiani & Quistorff (2016) show two calculations for *p-values*. The first (illustrated below) is a two-sided *p-value*:

$$p - value = Pr(|\underline{\alpha}_{1t}^{PL}| \geq |\underline{\alpha}_{1t}|) = \frac{\sum_{j \neq 1} 1(|\underline{\alpha}_{jt}| \geq |\underline{\alpha}_{1t}|)}{J}$$

where  $\underline{\alpha}_{1t}^{PL}$  is the specific placebo effect of the number of possible placebo averages,  $\underline{\alpha}_{1t}$  is the actual treatment effect at time  $t$ , and  $J$  is the total number of donors. The *p-value* in SCM should be interpreted as the proportion of control units that have an estimated placebo effect that is at least as large as the actual treatment. *P-values* indicate the extent to which the actual treatment occurred by chance. Therefore, *p-values* closer to zero indicate greater confidence in the actual treatment effects. Specifically, low *p-values* suggest a low probability that the actual treatment effect occurred by chance. Conversely, high *p-values* (i.e., those closer to one) suggest lower confidence in the actual treatment effects, suggesting a higher probability that the actual treatment effects occurred by chance.

### **Appropriateness of SCM**

As has been described, SCM has been viewed by researchers as an appropriate technique to analyze the effect of policies, programs, events, interventions, and rare

idiosyncratic phenomena. Specifically, SCM can estimate an appropriate counterfactual when other statistical methods fall short (Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015). Indeed, researchers have used other quasi-experimental techniques, the most common being the difference-in-differences (DID) technique, to estimate treatment effects. The DID approach approximates a counterfactual based on the behavior of a set of comparison units, similar to SCM. However, the DID technique is limited in ways that make it inappropriate for a study on RCM for several reasons worth noting.

First, the DID approach is limited because it cannot account for the effects of time-variant unobserved variables on the dependent variable (Abadie et al., 2010). Specifically, this means that the DID technique would produce a biased comparison group and a biased counterfactual (i.e., what would have been observed by the treated unit in the absence of the treatment) by extension (Abadie et al., 2010, 2015). With respect to this limitation, the DID approach would not be appropriate for a study RCM for three reasons: (1) RCM is a very nuanced budget model such that no one institution operates it the same way; (2) universities may modify their RCM models during a sample period of a study; and (3) RCM has been adopted across various years (Hearn et al., 2006; Jaquette et al., 2018). Specifically, each of these three reasons may affect the time-variant unobserved factors that may impact a given outcome variable. Therefore, the inability of DID to account for unobserved variables over time will likely bias the comparison group and post-treatment counterfactual.

A key feature of SCM can address this limitation of DID, however. Specifically, SCM allows the effects of observed and unobserved variables to vary over time (Abadie et al., 2010). With regard to a study on RCM – as evidenced by Jaquette et al. (2018) –



this feature of SCM is attractive because it allows the researcher to approximate a reliable control group and post-treatment counterfactual by extension.

The DID technique is also limited because it estimates *average* treatment effects. This feature of DID is particularly not useful for a study on RCM because there are so few known colleges and universities that have implemented RCM relative to the total number of colleges and universities. For example, as noted by Curry et al. (2013) and Jaquette et al. (2018), there are fewer than 60 known colleges and universities that have fully adopted RCM. In that respect, the DID technique would be inappropriate for a study on RCM because an *average* treatment effect of RCM may likely be biased toward zero. For example, the treatment effect of “good” RCM models (where there may be positive effects) may be overrun by the effect of ineffective RCM models (where there may be negative treatment effects) after computing the *average* treatment effect over a relatively small number of institutions that use RCM (Jaquette et al., 2018). This limitation extends to other quasi-experimental approaches, such as propensity score matching and instrumental variables (IV) regression – both of which also estimate *average* treatment effects.

However, with regard to this limitation of DID and other quasi-experimental approaches, two key features of SCM make it more attractive for a study on RCM. First, SCM calls for smaller sample sizes and allows the researcher to select the treated and untreated units without random or probabilistic sampling techniques (Abadie & Gardeazabal; Abadie et al., 2010, 2015). Specifically, due to the small number of institutions that have adopted RCM, DID would perhaps produce more accurate results (i.e., *average* treatment effects) if there are more RCM institutions in the study.

Specifically, there would be more institutions with which to estimate an *average* treatment effect. Additionally, the second notable feature of SCM is that it estimates the treatment effects of one case at a time (Adhikari et al., 2018). This feature is particularly useful for studies on RCM due to the relatively few institutions that have adopted it. Specifically, by estimating the treatment effects of one case at a time, SCM would estimate the actual treatment effect versus an *average* treatment effect (Abadie et al., 2010; Adhikari et al., 2018). Therefore, the results of a SCM analysis would be more precise than the DID approach.

Additionally, the DID technique is limited in its ability to approximate the extent to which the comparison unit (i.e., the control group) resembles the treated unit in the pre-treatment period (i.e., prior to the treatment). Theoretically, using DID, this suggests that a researcher could produce a biased control group and therefore estimate a biased *average* treatment effect. This limitation is inappropriate for a study on RCM due to the variability that exists among institutions that use RCM, noted above. However, unlike DID, the SCM technique can account for this limitation. Specifically, the SCM generates weights that illustrate the extent to which untreated units and their corresponding predictor variables resemble the treated unit and its corresponding predictor variables (Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015). In other words, SCM provides the researcher with information on how well the set of comparison units resemble the treated unit in the pretreatment period and what variables possess the most explanatory power (Abadie et al., 2015).

The DID approach is also limited as a consequence of one of its key assumptions – that is, the parallel trends assumption. This assumption requires the difference between

the treated unit and the post-treatment counterfactual to be constant over time. This feature of DID is particularly not appropriate for a study on RCM because year-to-year differences between the treated unit and the post-treatment counterfactual are possible. Specifically, in a study on RCM's impact on tuition revenue, Jaquette et al. (2018) revealed different year-to-year treatment effects for three of the four institutions in the study. This would violate the parallel trends assumption of the DID approach. However, SCM does not possess the same assumption or restriction as shown by researchers using SCM to estimate multi-year treatment effects.

In addition to the DID approach and other quasi-experimental methods, traditional regression techniques also are inappropriate for a study on the effects of RCM on total operating costs. For example, in a study on the effects of Proposition 99, a tobacco control program implemented in California in 1988, Abadie et al. (2010) used SCM to estimate that by the year 2000, per-capita cigarette sales were 26 packs lower than what they would have been in the absence of Proposition 99. A similar study on Proposition 99 was conducted by Fichtenberg and Glantz (2000) using least-squares regression. Fichtenberg et al. (2000) found that smoking consumption had been reduced after Proposition 99 at a rate of 0.67 fewer packs per year between 1993 and 1997. This would translate to about 14 fewer packs per year by the year 2000, which is substantially below what Abadie and colleagues found. Abadie et al. (2010) suggest that the resulting difference in their finding and that of Fichtenberg et al. (2000) was due to the inability of regression to appropriately generate a comparison group. As described above, SCM generates weights that range from zero to one and sum to one based on the extent to which untreated units resemble the treated unit in the pretreatment period. This allows the

researcher to appropriately select a viable comparison group and counterfactual by extension.

However, in generating a comparison group, regression techniques do not restrict the linear combination of coefficients (i.e., covariates/predictor variables) to remain between zero and one, nor do they sum to one (Abadie et al., 2010, 2015). This, in turn, requires the regression model to extrapolate beyond the available data to generate a comparison group and it does not allow the researcher to discern which comparison units (and predictor variables) possess the most explanatory power (Abadie et al., 2015). Considering the importance of generating a viable control group when estimating treatment effects, as explained above, regression techniques, too, are not appropriate for a study on the effects of RCM.

## **Methodological Approach in Context**

### **Theoretical Framework**

This study is guided by two theoretical frameworks: principal-agent theory (PAT) and Bowen's (1980) revenue theory of cost, as described in *Chapter 2: Literature Review*. Using the SCM procedure, these theoretical perspectives guided the selection of data, including the predictor variables used to generate a synthetic control unit for each of the two universities in this study, as well as the explanation of how RCM impacted total operating costs at each of the two universities in the study.

PAT frames the principal-agent relationship between central administration and deans (i.e., the leaders of academic responsibility centers) at two public research universities that have adopted RCM – consistent with previous research (Jaquette et al.,

2018). Specifically, I argue that under RCM, the goal of principals (i.e., central administration), in addition to increasing revenue (as has been explored by scholars), is also to minimize costs (Deering & Sá, 2014; Jaquette et al., 2018).

Bowen's (1980) revenue theory of costs theoretically frames the impact of revenues on costs. Specifically, this study incorporated variables on college and university revenue sources because RTC suggests that colleges and universities raise revenue and spend it all (i.e., revenues impact costs).

### **Sample Selection**

The University of New Hampshire (UNH) and the University of Arizona (UofA) were selected for several reasons. First, the leaders of each of these institutions cited (among others) that their motivation to implement RCM was to incentivize cost minimization across their respective institutions. Because universities that use RCM have cited different reasons for implementing it, the intent of university leaders at UNH and UofA to implement RCM as a means to minimize costs was a key factor in selecting them. Secondly, these institutions were selected because there was adequate public data available with regard to how both UNH and UofA operate their RCM models. Additionally, there was sufficient public record available on each of the institutions' websites to understand the context in which these universities operated when they implemented RCM. An adequate public record was not available on the websites or in the records of other universities that were considered for this study. Third, as illustrated in Table A2, each of these institutions has different levels of experience with RCM – specifically, UNH adopted RCM in the year 2000 and UofA adopted RCM in 2015. Fourth, each university implements RCM differently – that is, they employ different

funding formulas and allocation rules. Finally, the synthetic control method (the method used in this study) allows the researcher to assess the treatment effects of one unit (i.e., university) at a time. Therefore, the number of cases that are selected by the researcher is inconsequential (i.e., there is no minimum or maximum number required).

### **Data and Variables**

This study utilizes two institution-level datasets (one for each university in the study) to address the research question. Two institution-level datasets were used to account for the different sample periods (described below) of UNH and the UofA. The outcome variable is total operating costs and is defined as the sum of expenditures on academic administration, institutional administration, instruction, and student services. The predictor variables in this study have been adopted from previous research on higher education costs (see Table A3). Specifically, these empirical studies (e.g., Archibald & Feldman, 2018; Brinkman, 1981, 2000, 2006; Cohn, et al., 1989; deGroot et al., 1991; Doyle, 2015; Laband & Lentz, 2003; Robst, 2001; Sav, 2004; Titus et al., 2017) have revealed several determinants of costs (e.g., institutional size, institution scope, undergraduate versus graduate education costs (i.e., level of instruction), academic program mix, and revenues) that are used in this study. Specifically, to represent institutional size, institution scope, and level of instruction (as described in *Chapter 2: Literature Review*), the following variables were gleaned from previous research: full-time equivalent undergraduate enrollment, graduate headcount, the number of full-time faculty, research expenditures, and the average faculty salary. Additionally, to represent academic program mix, the proportion of students graduating with degrees in science, technology, engineering, and mathematics (STEM) out of the total number of graduates

was included. Finally, to understand the relationship between revenue and costs, as guided by Bowen's (1980) revenue theory of costs, the following revenue variables were included: tuition and fee revenue, state appropriations, private gifts, grants, and contracts, the proportion of tuition and fee revenue out of total revenue, and the proportion of state appropriation revenue out of total revenue.

As illustrated by Table A3, the primary source of these data is from the National Center for Education Statistics Integrated Postsecondary Education Data System (IPEDS). Secondly, information about the RCM funding formulas and historical accounts of RCM at the two respective public research universities in this study came from publicly available reports, letters, and websites.

Lastly, for the purposes of generating a viable donor pool (and synthetic control unit by extension) for each of the universities in the study, I excluded all universities suggested by Jaquette et al. (2018). Specifically, I excluded from the donor pool all institutions that have adopted RCM (see Table A1), including the universities in states that experienced "idiosyncratic shocks" such as all public research universities in Louisiana as a result of Hurricane Katrina, all public research universities in Colorado due to the state's change in how public higher education is funded, and Arizona State University was excluded due to the institution's expansion of the "New American University" initiative. The purpose of excluding these institutions was to ensure the donor pool, synthetic control unit, and post-treatment counterfactual were not biased.

## **Procedure**

As described above, the SCM procedure is conducted as follows: (1) estimate a synthetic control unit based on the weights of the untreated units in the donor pool; (2)

assess the treatment effects (if any) by generating a counterfactual for each time period in the post-treatment period and subtracting the outcome of the treated unit from the outcome of the synthetic control unit; and (3) and conduct placebo tests to discern the robustness of the findings. However, prior to SCM analysis, I first prepared the data by building two separate datasets – one for each of the universities in this study. Thus, the procedure that is described below was conducted twice – once for each of the two institutions in this study.

**Prepare the Data for Analysis.** First, to generate a donor pool, I accessed IPEDS and extracted the data to include all public universities in the United States that possess a doctoral university Carnegie classification with moderate research activity, higher research activity, and highest research activity. The Carnegie classification for selecting doctoral universities to be a part of the donor pool differs for UNH and UofA to account for the different sample periods.

Specifically, the Carnegie classification for selecting doctoral universities for the UNH dataset is based on the 2000 classification. This generated an original list (i.e., before data cleaning) of 165 institutions, including UNH. The Carnegie classification for the UofA dataset is based on the 2015 classification. This generated an original list (i.e., before data cleaning) of 195 institutions, including UofA. Thereafter, I selected the appropriate variables in the study as listed in Table A3 from the sample years for each university in this study (described below).

**Sample Periods.** The University of New Hampshire officially implemented RCM in 2000. The entire sample period for UNH is 1989-90 to 2004-2005. The pre-treatment period begins in 1989-90 and ends the year prior to RCM implementation at UNH, 1998-



99. The post-treatment period includes each year after RCM implementation for five years. A five-year post-treatment period is selected for two reasons: (a) consistent with prior research (Hearn et al., 2006; Jaquette et al., 2018); and (b) the UNH reviewed and modified its original RCM formulas and policies after the fifth year. Therefore, for consistency, I evaluated the treatment effects of RCM on total operating costs in 2000-01, 2001-02, 2002-03, 2003-04, and 2004-05.

The University of Arizona implemented RCM in 2015. Thus, the RCM model is relatively new and does not have many post-treatment observations due to data availability. The overall sample period begins in 1989-90 and ends in 2017-18 (the most recently available data in IPEDS). The pre-treatment period extends from 1989-90 and ends in 2013-14 (i.e., the year prior to RCM implementation). The treatment effects were evaluated for three years: in 2015-16, 2016-17, and 2017-18. Three years of post-treatment analysis was sufficient to assess robust treatment effects, as will be described in *Chapter 4: Results*.

**Data Cleaning.** After downloading the data from IPEDS into Microsoft Excel, I used the criteria listed by Jaquette et al. (2018) (described above) for excluding institutions from the donor pool. Additionally, I excluded institutions that were missing data for any of the variables across the sample years in the study. As described by Abadie et al. (2010, 2015) and Galiani and Quistorff (2016), SCM requires a strongly balanced dataset to create a viable synthetic control unit and counterfactual by extension. For UNH, these data cleaning exercises reduced the dataset from 165 institutions to 133 institutions, including UNH. With regard to UofA, these exercises reduced the dataset from 195 institutions to 127 institutions.

Lastly, I imported the data from Microsoft Excel to the statistical software Stata. The data were transformed from a wide format to a long format to allow for the analysis of the cross-sectional time-series data. Using the **tsset** command in Stata, I declared the data to be time-series data – a requirement to conduct the SCM analysis (described below). After declaring the dataset as time-series (i.e., the **tsset** command in Stata), I conducted the data analysis.

**Data Analysis.** The data were analyzed in three phases: descriptive analysis, SCM analysis, and placebo tests, and sensitivity analysis for robustness. First, I conducted some descriptive data analysis by generating the means, standard deviations, ranges, medians, and percentiles of all variables in the dataset for each of the institutions in this study and across each of their respective sample periods.

Next, using the **synth** command and syntax in Stata, I conducted a SCM analysis to generate a synthetic control unit. The **synth** command is a user-written command developed by Abadie, Hainmuller, and Diamond (2011). It allows the researcher to declare the dependent variable, the predictor variables, the treated unit, and the treatment period to generate the pre-treatment RMSPE and the synthetic control unit. The results of this command generated a list of the universities that make up the synthetic control unit, as well as their corresponding weights. The pre-treatment RMSPEs of each predictor variable also shows the extent to which each predictor variable of the synthetic control unit resembles the characteristics of the treated unit (see Table A3).

After the synthetic control unit was estimated using the **synth** command, I analyzed the treatment effects of RCM on total operating costs using the **synth\_runner** command in Stata. The **synth\_runner** command was developed by Galiani et al. (2016)

and allows the researcher to run multiple synthetic control estimations, calculate the treatment effects of multiple post-treatment years, and conduct in-space placebo tests simultaneously.

After running the **synth\_runner** command, which provided the treatment effects for each year of the post-treatment period and in-place (across-unit) placebo test results, I conducted sensitivity analysis called the leave-one-out test. The leave-one-out test allowed me to remove the most critical synthetic control (i.e., the university with the highest weight  $w$ ) from the synthetic control unit and rerun the **synth\_runner** command. I compared the line plots of the cost trends and post-treatment RMSPE generated by the **synth\_runner** command from the original SCM analysis with the line plots of the cost trends and post-treatment RMSPE of the sensitivity analysis to make a determination on the robustness of the findings. The main results of the study are discussed in the next chapter; the sensitivity analysis is depicted in Appendix B.

## **Limitations**

This study was designed to shed light on RCM's effect regarding total operating costs at two public research universities in the United States. However, this study is limited with regard to data availability and with regard to the methodological approach.

Regarding data availability, this study is limited because data at the academic-unit (e.g., college or school) level are unavailable. Due to the lack of available data at the academic unit level, this study cannot reveal how RCM might have impacted operating costs at the colleges and schools within the universities in the study. As has been noted, RCM incentivizes (among other goals) cost minimization at the academic unit level (e.g.,

schools, colleges, and departments) through the use of funding formulas and devolved financial responsibility (Curry et al., 2013; Strauss & Curry, 2002; Whalen, 1991).

However, because academic-unit level data are reported in aggregate, this study assumes implicitly that the impact of RCM on total operating costs are revealed in the aggregate as well.

In addition to data availability at the academic-unit level, this study is limited due to the lack of data that defines which institutions have fully implemented RCM. This limitation has methodological implications as well. Specifically, this study excludes institutions from the donor pool that have fully implemented RCM under a formal review process commissioned by the president or provost of the university. However, as described above, the SCM technique requires the researcher to identify a donor pool of untreated units in order to generate a viable synthetic control unit. Because there is no central database of institutions that use RCM, it is possible that the donor pools that were used to generate a synthetic control unit for each of the two universities in this study included some institutions that use RCM. This could potentially produce biased estimates. To mitigate the possibility, all known RCM universities were excluded from the donor pool. The list of known RCM universities was developed by Curry et al. (2013), adopted by Jaquette et al. (2018), and supplemented using reports and websites (see Table A1).

In addition to the data limitations, this study is limited methodologically for at least two reasons. First, the synthetic control method cannot account for idiosyncratic shocks that may occur around the treatment date for a unit under investigation (Adhikari, Duval, Hu, & Loungani, 2018). As noted previously, all untreated units could,

theoretically, be removed from the donor pool to improve the estimation of pretreatment and post-treatment counterfactual. However, any shocks caused by random events to the treated unit cannot be controlled for using SCM. Secondly, SCM is limited because it does not address all sources of endogeneity such as reverse causality (Adhikari et al., 2018). Indeed, one of the key assumptions in SCM is that all predictor variables are both independent of the treatment and independent of the error term. However, Abadie et al. (2010) proved that SCM can substantially reduce endogeneity caused by omitted variable bias. Specifically, SCM (as noted above) can take into account time-varying unobserved confounders when estimating an appropriate synthetic control unit and counterfactual by extension. Despite these limitations, however, SCM is the most appropriate technique to address the research question, as shown in the *Appropriateness* section above.

## **Chapter 4: Results**

### **Introduction**

This study examines the impact of Responsibility Center Management (RCM) on costs at two public research universities in the United States: the University of New Hampshire and the University of Arizona. These two institutions of higher education sought and implemented RCM for several reasons, however, the most salient among them was to minimize costs. This chapter describes the results of the synthetic control analysis that was conducted to investigate the extent to which RCM impacted total operating costs. The analysis and results will be discussed below.

### **Findings**

#### **University of New Hampshire**

Founded in 1866, the University of New Hampshire (UNH) is a public research university located in Durham, New Hampshire. UNH is the state flagship institution and currently enrolls over 13,000 undergraduates and over 2,000 graduate students across 13 colleges and schools (UNH Facts and Figures, 2019). UNH implemented RCM on July 1, 2000, after an 18-month RCM exploration study was conducted at the request of the then university president Joan Leitzel. President Leitzel cited five reasons for moving the campus to RCM. Among them she noted “[t]here will be stronger incentives for cost effectiveness and revenue generation” (Joan Leitzel, personal communication, January 14, 2000) because the university had experienced significant changes in enrollment, total operating costs, and total revenue prior to the implementation of RCM.

## **Descriptive Statistics**

Table 4.1A illustrates descriptive statistics of key variables of the University of New Hampshire over the pretreatment period of the study (i.e., 1990-1999). Table 4.1B shows the values of each variable during the treatment period (i.e., the year 2000) and each of the post-treatment periods (i.e., 2001 through 2005). As shown in Table 4.1A, the average total operating costs over the pretreatment period was \$98.26 million and ranged from \$76.27 million to \$116.69 million. In the treatment year, as illustrated in Table 4.1B, operating costs were \$120.09 million. Operating costs rose in current dollars (i.e., not adjusted for inflation) each year after RCM had been implemented. Specifically, after the first year of RCM implementation, operating costs rose to \$125.41 million and continued to rise thereafter. For example, operating costs went from \$139.13 million in 2002 to \$167.86 million in 2005.

The average number of full-time equivalent (FTE) undergraduate students was 10,776 and ranged from 9,914 to 11,496 in the pretreatment period (see Table 4.1A). During the treatment- and post-treatment periods, the number of FTE undergraduate students increased each year between 2000 and 2004 (see Table 4.1B). Specifically, FTE undergraduates rose from 10,878 in 2000 to 11,692 in 2004. However, undergraduate enrollment decreased between 2004 and 2005.

The number of graduate students ranged from 1,960 to 2,936 and averaged at 2,936 over the pretreatment period of the study (see Table 4.1A). UNH enrolled 2,784 graduate students when RCM was implemented in 2000. Similar to undergraduate enrollment, the number of graduate students fluctuated over the post-treatment period.

Despite fluctuating enrollment between this period, UNH enrolled more graduate students in 2005 than in 2001.

Between 1990 and 1999, the average number of faculty at UNH was 589. As shown in Table 4.1B, the number of full-time faculty grew from 592 in 2000 to 665 in 2005. Similarly, the average nine-month equated faculty salary was \$46,464 in the pretreatment period and increased each year after RCM had been implemented. Specifically, the average faculty salary rose in current dollars from \$56,072 in 2000 to \$75,273 in 2005.

The average research expenditures at UNH was \$41.99 million prior to RCM implementation. Indeed, research expenditures ranged from \$27.91 million to \$53.36 million over the pretreatment period. Research expenditures increased each year in current dollars between 2000 and 2004, peaking at \$93.89 million in 2004.

Nearly 28% of bachelor's degrees conferred by UNH between 1990 and 1999 were from a science, technology, engineering, and/or mathematics (STEM) field on average. This percentage ranged from 25% to 30.8% over the pretreatment period. The percentage of STEM bachelor's degrees conferred fluctuated between 2000 and 2005. Specifically, the percentage of STEM degrees decreased from 27.4% in 2000 to 23.8% in 2003 but increased from 2003 to 2004. Between 2004 and 2005, the percent of STEM degrees decreased again from 26.2% to 24.6% respectively.

Similar to the variables for enrollment, faculty, and the number of STEM degrees conferred, the revenue predictor variables fluctuated over the study period. The average tuition and fee revenue in the pretreatment period was \$85.68 million. Tuition revenue represented 34.7% of total revenue at UNH over the same period. Both tuition and fee



revenue and the proportion of tuition and fee revenue out of total revenue increased between 2000 and 2005. Specifically, tuition and fee revenue rose in current dollars from \$114.18 million in 2000 to \$146.14 million in 2005. This corresponded with an increase in the proportion of tuition and fee revenue out of total revenue from 33.9% in 2000 to 35.1% in 2005.

Revenue from state appropriations also increased over the study period. For example, during the pretreatment period, the average state appropriation was \$42.78 million and ranged from \$35.31 million to \$48.81 million. State appropriations increased in current dollars from \$51.14 million in 2000 to \$58.24 million in 2005, after RCM had been implemented. However, the proportion of state appropriations out of total revenue decreased. The average proportion of state appropriations from total revenue at UNH was about 17.5% over the pretreatment period. After RCM was implemented, the proportion of state appropriations decreased from 15.2% in 2000 to 13.8% in 2005.

Lastly, revenue from private grants, gifts, and contracts ranged from \$8.84 million to \$19.13 million throughout the pretreatment period of the study. After RCM was implemented in 2000, revenue from private grants, gifts, and contracts decreased in current dollars from \$23.40 million in 2000 to \$9.02 million in 2005.

Table 4.1A Descriptive Statistics – University of New Hampshire (Pre-treatment Period 1990-1999)

<b>Predictor Variables</b>	<b>N</b>	<b>Mean</b>	<b>SD</b>	<b>Min.</b>	<b>25th Percentile</b>	<b>Median</b>	<b>75th Percentile</b>	<b>Max</b>
Total Operating Costs (outcome variable) (in millions)	10	\$98.26	\$13.91	\$76.27	\$84.19	\$100.12	\$108.15	\$116.69
Full-time Equivalent (FTE) Undergraduate Enrollment	10	10,776	483	9,914	10,483	10,788	11,183	11,496
Graduate Enrollment (headcount)	10	2,468	369	1,960	2,181	2,364	2,894	2,936
Full-time Faculty	10	589	20	558	573	591	606	615
Research Expenditures (in millions)	10	\$41.99	\$7.86	\$27.91	\$37.86	\$42.88	\$47.14	\$53.36
Average Faculty Salary (9-month equated salary)	10	\$46,464	\$15,809	\$3,043	\$46,194	\$51,252	\$53,346	\$57,740
Percent (%) of STEM bachelor's degrees produced out of total conferred	10	27.6	2.2	25.0	25.2	27.5	29.3	30.8
Tuition and Fee Revenue (in millions)	10	\$85.68	\$15.91	\$59.83	\$73.01	\$89.09	\$98.69	\$104.84
State Appropriation Revenue (in millions)	10	\$42.78	\$4.88	\$35.31	\$38.22	\$44.40	\$46.45	\$48.81
Revenues from Private Gifts, Grants, and Contracts (in millions)	10	\$15.35	\$3.76	\$8.84	\$11.67	\$17.00	\$18.72	\$19.13

<b>Predictor Variables</b>	<b>N</b>	<b>Mean</b>	<b>SD</b>	<b>Min.</b>	<b>25th Percentile</b>	<b>Median</b>	<b>75th Percentile</b>	<b>Max</b>
Percent (%) of Tuition and Fee Revenue out of Total Revenue	10	34.7	0.9	33.3	34.3	34.7	35.1	36.4
Percent (%) of State Appropriation Revenue out of Total Revenue	10	17.5	1.2	16.0	16.6	17.3	18.0	19.8

Table 4.1B Descriptive Statistics – University of New Hampshire (Treatment and Post-treatment Periods)

<b>Variable</b>	<b>Treatment Period</b>		<b>Post-Treatment Period</b>			
	<b>2000</b>	<b>2001</b>	<b>2002</b>	<b>2003</b>	<b>2004</b>	<b>2005</b>
Total Operating Costs (outcome variable) (in millions)	\$120.09	\$125.41	\$139.13	\$144.69	\$162.25	\$167.86
Full-time Equivalent (FTE) Undergraduate Enrollment	10,838	10,873	11,066	11,618	11,692	10,973
Graduate Enrollment (headcount)	2,784	2,790	2,707	2,884	3,018	2,988
Full-time Faculty	592	599	605	610	651	665
Research Expenditures (in millions)	\$64.49	\$72.94	\$75.10	\$83.02	\$93.89	\$89.02
Average Faculty Salary (9-month equated salary)	\$56,072	\$61,417	\$66,762	\$69,895	\$71,513	\$75,273
Percent (%) of STEM bachelor's degrees produced out of total conferred	27.4	26.0	24.7	23.8	26.2	24.6
Tuition and Fee Revenue (in millions)	\$114.18	\$120.56	\$126.92	\$134.25	\$146.14	\$146.14
State Appropriation Revenue (in millions)	\$51.14	\$53.75	\$56.47	\$57.22	\$56.76	\$58.24

Variable	Treatment Period		Post-Treatment Period			
	2000	2001	2002	2003	2004	2005
Revenue from Private Gifts, Grants, and Contracts (in millions)	\$23.40	\$23.75	\$10.95	\$9.59	\$9.25	\$9.02
Percent (%) of Tuition and Fee Revenue out of Total Revenue	33.9	33.8	35.2	36.6	35.6	35.1
Percent (%) of State Appropriation Revenue out of Total Revenue	15.2	15.1	15.6	15.6	13.8	13.8

### Synthetic University of New Hampshire

Using the synthetic control method, specifically the *synth* command in Stata, I estimated a control group known as the synthetic control unit by identifying donor units (untreated units) from the donor pool who's predictor variables best resembled the pretreatment characteristics (predictor variables) of the treated unit. Specifically, the synthetic control method assigned a weight ( $w$ ) to each of the units in the donor pool. The weights ranged from zero to one and summed to one. Donor units with weights above zero were selected to be a part of the synthetic control unit.

Table 4.2 shows the composition of the synthetic control unit for UNH. The synthetic control unit was estimated using the *synth* command in Stata. Hereafter the synthetic control unit for UNH is referred to as Synthetic University of New Hampshire or Synthetic UNH. Synthetic UNH is composed of seven universities: University of Vermont, Montana State University, Central Michigan University, North Dakota State University, College of William and Mary, Mississippi State University, and the University of Massachusetts Lowell. The weighted characteristics (predictor variables) of Synthetic UNH were used to estimate a pretreatment root mean square prediction error

(RMSPE) and a post-treatment counterfactual for each period after RCM was implemented.

The University of Vermont possesses the most predictive power (over 47%) for operating costs at UNH because the University of Vermont’s pretreatment characteristics most closely resemble those of UNH. This means, for example, that the predictor variables for the University of Vermont will provide the most influence on estimating the pretreatment RMSPE and the post-treatment counterfactual for each period. Below, I describe the pretreatment data analysis and treatment effects.

Table 4.2 Synthetic Control Unit for University of New Hampshire (Synthetic UNH)

<b>UnitID</b>	<b>Institutions (synthetic controls)</b>	<b>State</b>	<b>Weight (<math>w</math>)</b>
231174	University of Vermont	VT	0.471
180461	Montana State University	MT	0.197
169248	Central Michigan University	MI	0.12
200332	North Dakota State University-Main Campus	ND	0.087
231624	College of William and Mary	VA	0.081
176080	Mississippi State University	MS	0.022
166513	University of Massachusetts-Lowell	MA	0.021

### **Analysis of Pre-treatment Data**

After the synthetic control unit was estimated, I used the SCM to approximate: (1) the predictor variable values for the synthetic control unit that produced the lowest pretreatment root mean square prediction error (RMSPE) and (2) the weights ( $v_k$ ) of each predictor variable in the analysis. Table 4.3 illustrates the predictor variable values for the University of New Hampshire and the estimated predictor variable values for Synthetic UNH (i.e., the control group). The predictor variable values for Synthetic UNH were estimated based on the weights ( $w$ ) from each synthetic unit (i.e., each university that is

part of Synthetic UNH). All predictor variables, including the outcome variable, total operating cost, were included over two different periods: 1991 and 1999. Consistent with other studies that employ SCM (Barone & Mocetti, 2014; Eren & Ozbeklik, 2016; Jaquette et al., 2018; Liu, 2015), year-specified variables were included in the analysis to produce the lowest possible pretreatment RMSPE. Possessing a low pretreatment RMSPE minimizes the difference between the treated unit and the synthetic control unit. In theory, the pretreatment predictor variables of UNH and Synthetic UNH two should be nearly identical. This, in turn, increases confidence in the post-treatment counterfactual.

The specific years of 1991 and 1999 were selected after a series of iterative exercises were conducted. Specifically, I included a year-specified variable for all predictor variables in the year preceding the treatment (i.e., 1999). Next, I used the *synth* command in Stata to identify which combination of other variables would produce the lowest pretreatment RMSPE. After testing over 20 different combinations of variables across different years, I concluded that including all predictor variables in 1991 and 1999 produced the lowest pretreatment RMSPE. Specifically, the pretreatment RMSPE produced by this set of predictor variables was 3.84. This means that the average difference in total operating costs between the treated unit and the synthetic control unit (Synthetic UNH) in the pre-treatment period is \$3.84 million. This pretreatment RMSPE represents less than four percent of UNH's pretreatment average total operating costs. Thus, the difference in operating costs between the treated unit (UNH) and the synthetic control unit (Synthetic UNH) is trivial. This suggests a good pretreatment fit and increases confidence in the estimated synthetic control unit (i.e., Synthetic UNH).

Table 4.3 also shows the average predictor variable values of the unweighted donor pool. The donor pool predictor variable values are shown in Table 4.3 to illustrate that the synthetic control unit is a better control group than the unweighted donor pool. For example, by comparing the values of the predictor variables for UNH to the estimated predictor variables of Synthetic UNH and the predictor variables of the unweighted donor pool, it is clear that the Synthetic UNH is a better control group than the unweighted donor pool. For example, the outcome variable for total operating costs in 1991 is \$82.06 million for UNH, \$82.87 million for Synthetic UNH, and \$129.50 million for the donor pool. Therefore, the donor pool, if used as the control group for UNH, would produce a poor pretreatment fit (and post-treatment counterfactual by extension).

Table 4.3 also shows the weights ( $v_k$ ) of each predictor variable in the analysis. Each weight ( $v_k$ ) describes how well each predictor variable predicts the outcome variable (total operating costs). The value of the weights ( $v_k$ ) ranges from zero to one and sum to one. Predictor variables with weights closer to one possess higher predictive power than those closer to zero. As shown in Table 4.3, the outcome variables for total operating costs possessed the most predictive power over the pretreatment period: 0.408 (40.8%) for 1991 and 0.541 (54.1%) for 1999. The amount of research expenditures is the next best predictor of total operating costs. However, research expenditures, as well as the remaining predictor variables, including the financial variables (e.g., tuition and fee revenue, state appropriations, and private gifts, grants, and contracts) each represent less than one percent of predictive power for total operating costs.

Table 4.3 University of New Hampshire Pre-treatment Estimates

<b>Predictor Variable</b>	<b>University of New Hampshire (Treated Unit)</b>	<b>Synthetic University of New Hampshire (Control Unit)</b>	<b>Donor Pool (n=132)</b>	<b>Predictor Variable Weights (<math>v_k</math>)</b>
Total Operating Cost (USD in millions) (1991)	\$82.06	\$82.87	\$129.50	0.4080
Total Operating Cost (USD in millions) (1999)	\$116.69	\$118.26	\$186.83	0.5410
Full-time Equivalent (FTE) Undergraduate Enrollment (1991)	10,197	8,838	12,843	0.0050
Full-time Equivalent (FTE) Undergraduate Enrollment (1999)	10,772	8,930	12,949	0.0050
Graduate Enrollment (headcount) (1991)	2,116	1,395	3,866	0.0010
Graduate Enrollment (headcount) (1999)	2,718	2,087	4,009	0.0000
Percent (%) of STEM bachelor's degrees produced out of total conferred (1991)	25.0	26.9	25.1	0.0000
Percent (%) of STEM bachelor's degrees produced out of total conferred (1999)	27.8	28.0	27.1	0.0000
Full-time Faculty (1991)	558	538	770	0.0020
Full-time Faculty (1999)	609	514	760	0.0040
Average Faculty Salary (9-month equated salary) (1991)	\$44,849	\$42,602	\$44,483	0.0010
Average Faculty Salary (9-month equated salary) (1999)	\$56,725	\$53,453	\$56,908	0.0010
Percent (%) of State Appropriation Revenue out of Total Revenue (1991)	19.0	26.2	41.3	0.0000
Percent (%) of State Appropriation Revenue out of Total Revenue (1999)	16.0	19.0	35.8	0.0010



<b>Predictor Variable</b>	<b>University of New Hampshire (Treated Unit)</b>	<b>Synthetic University of New Hampshire (Control Unit)</b>	<b>Donor Pool (n=132)</b>	<b>Predictor Variable Weights (<math>v_k</math>)</b>
Percent (%) of Tuition and Fee Revenue out of Total Revenue (1991)	33.3	28.6	17.8	0.0000
Percent (%) of Tuition and Fee Revenue out of Total Revenue (1999)	34.3	32.2	21.3	0.0010
Research Expenditures (USD in millions) (1991)	\$32.85	\$25.08	\$44.08	0.0070
Research Expenditures (USD in millions) (1999)	\$53.36	\$38.55	\$66.61	0.0070
Revenue from Private Gifts, Grants, and Contracts (USD in millions) (1991)	\$11.67	\$12.74	\$14.51	0.0040
Revenue from Private Gifts, Grants, and Contracts (USD in millions) (1999)	\$18.72	\$19.42	\$25.68	0.0020
State Appropriation Revenue (USD in millions) (1991)	\$36.99	\$38.32	\$107.71	0.0020
State Appropriation Revenue (USD in millions) (1999)	\$48.81	\$44.47	\$137.22	0.0020
Tuition and Fee Revenue (USD in millions) (1991)	\$64.60	\$53.67	\$42.90	0.0010
Tuition and Fee Revenue (USD in millions) (1999)	\$104.84	\$87.17	\$76.88	0.0050

## Treatment Effects

The University of New Hampshire implemented RCM in the year 2000.

Treatment effects on the impact of RCM on total operating costs at UNH were assessed each year for five years after RCM had been implemented. Figure 4.1 was generated using the *synth* command in Stata. Figure 4.1 illustrates the actual total operating costs at UNH and the estimated total operating costs for Synthetic UNH. As shown in Figure 4.1, total operating costs at UNH increased after RCM was implemented in the year 2000.

The synthetic control analysis was used to determine whether the increase in total operating costs at UNH was *caused* by RCM. Specifically, the synthetic control method estimated a post-treatment counterfactual (i.e., what would have occurred at UNH in the absence of RCM) for each year of the post-treatment period. Synthetic UNH in the post-treatment period represents what would have occurred at UNH if RCM had not been implemented. As shown in Figure 1.1, the estimated total operating costs at Synthetic UNH decreased initially after RCM had been implemented and then increased in the year 2004.

The treatment effects of RCM's impact on total operating costs at UNH were estimated using the *synth\_runner* command in Stata. Treatment effects are the difference between the actual total operating costs at UNH and the estimated total operating costs of Synthetic UNH. As illustrated in Table 4.4, the magnitude of the treatment effects ranged from \$600,000 to \$28.17 million over the five-year post-treatment period. Specifically, the results after the first year of RCM implementation show that total operating costs were \$600,000 higher than they would have been if RCM had not been implemented. However, in 2002, the magnitude of the treatment effect increased substantially.

Specifically, Table 4.4 illustrates that total operating costs were \$19.15 million higher at UNH compared to Synthetic UNH. This suggests that if RCM had not been adopted at UNH, total operating costs would have been lower.

The magnitude of the treatment effect increased between 2002 and 2003. Specifically, total operating costs at UNH increased from \$139.13 in 2002 to \$144.69 in 2003. However, the estimated total operating costs at Synthetic UNH decreased from nearly \$120 million in 2002 to \$116.5 million in 2003. This resulted in a larger difference in operating costs between UNH and Synthetic UNH. That is, the magnitude of the treatment effect increased from \$19.15 million in 2002 to \$28.17 million in 2003. Again, the results suggest that RCM *caused* total operating costs to increase at UNH.

Between 2004 and 2005, the results also indicate that RCM impacted total operating costs, making them higher than they would have been if RCM had not been implemented. However, over the same period, the magnitude of the treatment effects declined. Specifically, between 2004 and 2005, the treatment effect of RCM on total operating costs decreased from \$16.49 million to \$15.69 million. While these results suggest generally that RCM positively impacted total operating costs, the declining magnitude of the treatment effects between 2004 and 2005 may suggest that total operating costs are shrinking as a result of RCM. However, an analysis of the magnitude of the treatment effects was not considered and go beyond the scope of this study. To assess the significance of the results, a series of placebo tests and sensitivity analyses were conducted. The results of the placebo tests and leave-one-out test are discussed next.

Figure 4.1 Graph of Treatment Effects of RCM's Impact on Operating Cost at University of New Hampshire

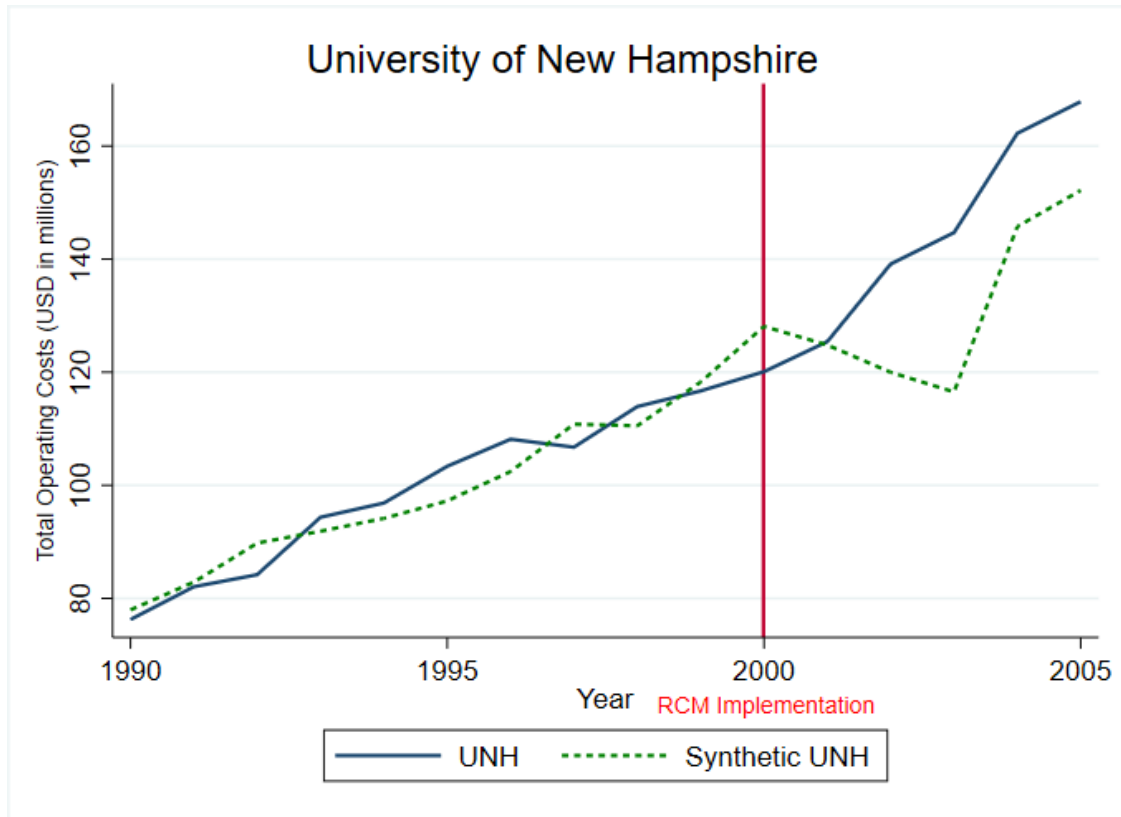


Table 4.4 Treatment Effects of RCM's Impact on Operating Cost at University of New Hampshire

Total Operating Costs (USD in millions)						
Post-Treatment Period	Year	UNH	Synthetic UNH	Treatment Effect (UNH - Synthetic UNH)	P-Value	
1	2001	\$125.41	\$124.81	\$0.60	0.939	
2	2002	\$139.13	\$119.99	\$19.15	0.227	
3	2003	\$144.69	\$116.52	\$28.17	0.212	
4	2004	\$162.25	\$145.77	\$16.49	0.417	
5	2005	\$167.86	\$152.16	\$15.69	0.432	

### Placebo Tests and Inference

A series of in-place (across-unit) placebo tests were conducted to obtain the *p-values* for each post-treatment period (see Table 4.4). Specifically, the *synth\_runner*

command artificially reassigned the RCM "treatment" to each of the 132 units in the donor pool and calculated a "placebo" effect for each donor unit across each post-treatment period. This means that 132 different placebo effects were estimated across each of the five years of the post-treatment period. Thereafter, the *synth\_runner* command estimated a cumulative distribution of "placebo" effects for each post-treatment year. Next, the analysis calculated the probability of obtaining a placebo effect that was greater than or equal to the actual treatment effect for each year. The results of these calculations are illustrated in Table 4.4.

*P-values* closer to zero indicate greater confidence in the treatment effect for each period. Conversely, high *p-values* (i.e., those closer to one) suggest lower confidence in the treatment effect for that period. As noted in *Chapter 3: Methodology*, *p-values* at or below the 10% threshold suggest that the treatment (i.e., implementation of RCM) had a significant causal effect on the outcome variable (i.e., total operating costs).

With regard to the UNH, none of the *p-values* reached a level of significance to conclude that RCM had a significant causal effect on total operating costs ( $p \leq 0.10$ ). For example, the estimated *p-value* after year one of RCM implementation is 0.939. This means that there is a 93.9% probability of obtaining a placebo effect that is as large or larger than the treatment effect after the first year of RCM implementation. Specifically, this means that there is a 93.9% probability that RCM's impact on total operating costs occurred by chance. Put another way, this *p-value* suggests that there is a 6.1% probability that the treatment effect of RCM *did not* occur by chance. Therefore, confidence is significantly lessened in the result for the first year after RCM had been

implemented. Specifically, this suggests that RCM did not cause total operating costs to be higher than they would have been if RCM had not been implemented.

Similarly, the *p-values* did not reach significance for the remaining years following RCM implementation. However, the *p-values* for these years (i.e., years two through five) show greater confidence that RCM impacted total operating costs compared to the first year. With regard to the second post-treatment period, the *p-value* suggests that there is a 27.7% probability that the treatment effect of RCM occurred by chance. In other words, there is a 72.3% probability that the treatment effect of RCM *did not* occur by chance. The *p-value* for period three suggests that there is a 21.2% probability that the treatment effect of RCM's impact on cost occurred by chance. Put another way, there is a 78.8% probability that the treatment effect of RCM *did not* occur by chance. The *p-value* for year four indicates that there is a 41.7% probability that the treatment effect of RCM's impact on cost occurred by chance. In other words, there is a 58.3% probability that the treatment effect of RCM *did not* occur by chance. Likewise, the *p-value* for period five suggests that there is a 43.2% probability that the treatment effect of RCM's impact on cost occurred by chance. This indicates that there is a 56.8% probability that the treatment effect of RCM *did not* occur by chance.

These results suggest that RCM positively impacted total operating costs but did *cause* total operating costs to be higher than if RCM had not been implemented.

Sensitivity analysis (i.e., the leave-one-out test) was conducted next to discern the robustness of the results.

## Leave-One-Out Test

The leave-one-out test was conducted to elucidate the robustness of the results. The leave-one-out test allows the researcher to remove a control (i.e., in this case, a university) from the synthetic control unit to determine if the main results hold (i.e., are the same) thereafter (Abadie et al., 2015; Jaquette et al., 2018; Krief et al., 2016). Ideally, the removal of any one control from the synthetic control unit should not significantly change the SCM results (e.g., the pretreatment estimation of the synthetic control unit, the post-treatment counterfactual(s), and treatment effects). However, if the results of the leave-one-out test are different from the main results, such that the main results were sensitive to the exclusion of any one control unit, then confidence in the main results is diminished. Conversely, if the results of the leave-one-out test are similar to the main findings, then confidence in the main findings is increased.

To conduct the leave-one-out test, I removed the most influential control unit from Synthetic UNH – specifically, the University of Vermont – and used the *synth* and *synth\_runner* commands in Stata to rerun the analysis. As described in Table 4.2, the University of Vermont possessed over 47% of explanatory power for UNH.

As illustrated in Appendix B, the leave-one-out analysis revealed that the main results of the study on UNH were not robust after the University of Vermont was removed from Synthetic UNH. Specifically, after the University of Vermont was excluded, the Synthetic UNH provided a poor pretreatment estimation of the treated unit. For example, as illustrated in Table B2 in Appendix B, a comparison of the pretreatment estimates of UNH, Synthetic UNH (with University of Vermont), and Synthetic UNH (without University of Vermont) illustrate that Synthetic UNH (without University of

Vermont) is a poor predictor of operating costs for UNH. This is further underscored by Figure B1 in Appendix B. Specifically, the difference in total operating costs between UNH and Synthetic UNH (with the University of Vermont removed) is significantly different from Figure 1.1 (without the University of Vermont removed). More specifically, the pretreatment RMSPE increased from \$3.84 million (without the University of Vermont removed) to \$15.6 million (with the University of Vermont removed).

Recall that the pretreatment RMSPE illustrates the average difference in operating costs between the treated unit and the synthetic control unit. Because \$15.6 million represents nearly 16% of the average pretreatment operating costs at UNH, it suggests a poor pretreatment fit – that is, the new Synthetic UNH (with the University of Vermont removed) does not provide an appropriate pretreatment estimation of UNH. As a consequence, confidence is diminished in the estimations of the post-treatment counterfactuals and treatment effects of both the leave-one-out test and the main SCM analysis (which includes the University of Vermont as part of Synthetic UNH).

The treatment effects that were estimated by the leave-one-out test are illustrated in Table B3 in Appendix B. Similar to the main findings of SCM analysis (which includes the University of Vermont as part of Synthetic UNH), the treatment effects estimated after the leave-one-out test suggest that RCM impacted total operating costs but not to a high enough level to infer causality. These treatment effects ranged from \$13.89 million to \$36.34 million and are consistent with the main SCM analysis.

However, although the treatment effects assessed by the leave-one-out test are similar to the main SCM results for UNH (which includes the University of Vermont),



the treatment effects of the leave-one-out should be interpreted with extreme caution because Synthetic UNH (with University of Vermont removed) represents a poor pretreatment fit as shown by Figure B1 and Table B2. Therefore, it is difficult to discern with confidence the extent to which there are similarities and differences between the treatment effects of the leave-one-out tests and the main SCM analysis.

The overall results of the leave-one-out test suggest that the University of Vermont is an influential control unit, such that when it is excluded from the synthetic control unit for UNH, it produces a poor pretreatment approximation of UNH. This implies that the main results regarding RCM's impact on total operating costs (which includes the University of Vermont) are sensitive to the exclusion of the University of Vermont as a predictor. Therefore, confidence in the main findings is diminished and should be interpreted with caution. A summary of these findings will be discussed at the end of the chapter.

### **University of Arizona**

Located in Tucson, Arizona, the University of Arizona (UofA) was established in 1885 and serves as the state of Arizona's flagship university. UofA is a public research university that enrolls over 45,000 undergraduate and graduate students across 40 colleges and schools, including two hospitals (University of Arizona, 2019). In 2018, the campus managed a nearly \$2.4 billion operating budget (University of Arizona, 2019). After over two years of feasibility testing between 2012 and 2014, RCM was fully implemented beginning in July 2015. Two of the three motivating factors listed in UofA's RCM implementation website illustrate the institution's desire to increase

transparency around revenues and costs, and the desire to grow revenue while also becoming more cost effective in the wake of significant financial changes at the university. The analysis below reveals evidence regarding RCM's impact on total operating costs.

### **Descriptive Statistics**

Table 4.5A illustrates descriptive statistics of key variables of the University of Arizona over the pretreatment period of the study (i.e., 1990-2014). Table 4.5B shows the values of each variable during the treatment period (i.e., the year 2015) and each of the post-treatment periods (i.e., 2016 through 2018). As shown in Table 4.5A, the average total operating costs over the pretreatment period was \$466.83 million and ranged from \$277.31 million to \$881.36 million. In the treatment year, as illustrated in Table 4.5B, operating costs were \$956.56 million. Operating costs rose in current dollars (i.e., not adjusted for inflation) after RCM had been implemented. Specifically, operating costs rose from \$956.56 million in 2015 to approximately \$1.08 billion in 2016. In 2017 and 2018, total operating costs were about \$1.07 billion and \$1.16 billion, respectively.

The average number of FTE undergraduate students was 25,231 and ranged from 22,615 to 29,491 in the pretreatment period (see Table 4.5A). During the treatment- and post-treatment periods, the number of FTE undergraduate students fluctuated (see Table 4.5B). Specifically, FTE undergraduates rose from 30,629 in 2015 to 30,842 in 2016. However, undergraduate enrollment decreased between 2016 and 2017 but increased again between 2017 and 2018.

The number of graduate students ranged from 6,870 to 8,951 and averaged at 7,616 over the pretreatment period of the study (see Table 4.5A). UofA enrolled 9,249

graduate students when RCM was implemented in 2015. Unlike undergraduate enrollment, the number of graduate students increased each year over the post-treatment period. Specifically, between 2016 and 2018, the number of graduate students rose from 9,264 to 9,650.

Between 1990 and 2014, the average number of faculty at UofA was 1,455. As shown in Table 4.5B, the number of full-time faculty grew from 1,583 in 2015 to 1,710 in 2018. The average nine-month equated faculty salary was \$70,474 in the pre-treatment period and increased each year after RCM had been implemented. Specifically, the average faculty salary rose in current dollars from \$92,727 in 2015 to \$98,087 in 2018.

The average research expenditures at UofA were \$292.37 million and ranged from \$140.84 million to \$486.27 million over the pretreatment period. Research expenditures continued to rise in current dollars each year between RCM implementation in 2015 and 2018, three years after RCM had been implemented. Specifically, research expenditures rose from \$476.55 in 2015 to \$497.69 in 2018.

Moreover, nearly 27.4% of bachelor's degrees conferred by UofA between 1990 and 2014 were from STEM fields. This percentage ranged from 24.2% to 31.2% over the pretreatment period. The percentage of conferred STEM bachelor's degrees fluctuated between 2015 and 2018 but generally increased. Specifically, the percentage of STEM degrees conferred increased from 31.2% in 2015 to 33.0% in 2016 but decreased from 2016 to 2017. Between 2017 and 2018, the percent of conferred STEM degrees increased again from 32.3% to 34.2% respectively.

Similar to the variables for enrollment, faculty, and the number of STEM degrees conferred, the revenue predictor variables fluctuated over the study period. The average

tuition and fee revenue in the pretreatment period was \$263.75 million. Tuition revenue represented 21.4% of total revenue at UofA over the same period. Both tuition and fee revenue and the proportion of tuition and fee revenue out of total revenue increased between 2015 and 2018. Specifically, tuition and fee revenue rose in current dollars from \$749.41 million in 2015 to \$867.56 million in 2018. This corresponded with an increase in the proportion of tuition and fee revenue out of total revenue from 36.7% in 2015 to 40.9% in 2018.

Revenue from state appropriations fluctuated over the study period. For example, during the pretreatment period, the average state appropriations was \$312.32 million and ranged from \$230.68 million to \$445.02 million. By the time RCM had been implemented at UofA, state appropriations were \$294.48 million, which was lower than the average state appropriations over the pretreatment period. State appropriations to UofA declined again from 2015 to 2016, but increased in current dollars from 2016 to 2018, as shown in Table 4.5B. Despite subtle fluctuations in the amount of state appropriations to UofA, the proportion of state appropriations out of total revenue decreased over the study period. The average proportion of state appropriations from total revenue at UofA was about 30% and ranged from 15.3% to 37.5% over the pretreatment period. After RCM was implemented, the proportion of state appropriations decreased from 14.4% in 2015 to 13.3% in 2018.

Lastly, revenue from private grants, gifts, and contracts ranged from \$35.41 million to \$96.2 million throughout the pretreatment period of the study. After RCM was implemented in 2015, revenue from private grants, gifts, and contracts decreased in current dollars from \$89.98 million in 2015 to \$81.75 million in 2018.

Table 4.5A Descriptive Statistics – University of Arizona (Pre-treatment Period 1990-2014)

<b>Variable</b>	<b>N</b>	<b>Mean</b>	<b>SD</b>	<b>Min.</b>	<b>25th Percentile</b>	<b>Median</b>	<b>75th Percentile</b>	<b>Max</b>
Total Operating Costs (outcome variable) (in millions)	25	\$466.83	\$176.28	\$277.31	\$323.76	\$425.66	\$563.48	\$881.36
Full-time Equivalent (FTE) Undergraduate Enrollment	25	25,231	2,203	22,615	23,215	24,727	26,509	29,491
Graduate Enrollment (headcount)	25	7,616	605	6,870	7,118	7,450	7,759	8,951
Full-time Faculty	25	1,455	94	1,364	1,442	1,537	1,348	1,593
Research Expenditures (in millions)	25	\$292.37	\$112.40	\$140.84	\$194.95	\$249.28	\$373.94	\$486.27
Average Faculty Salary (9-month equated salary)	25	\$70,476	\$16,462	\$37,356	\$58,552	\$72,045	\$86,448	\$92,880
Percent (%) of STEM bachelor's degrees produced out of total conferred	25	27.4	1.9	24.2	26.1	27.5	28.9	31.2
Tuition and Fee Revenue (in millions)	25	\$263.75	\$180.57	\$92.07	\$133.83	\$188.83	\$327.05	\$670.32
State Appropriation Revenue (in millions)	25	\$312.32	\$56.84	\$230.68	\$272.32	\$314.08	\$349.11	\$445.02
Revenues from Private Gifts, Grants, and Contracts (in millions)	25	\$60.69	\$17.88	\$35.41	\$45.17	\$56.80	\$75.61	\$96.20

<b>Variable</b>	<b>N</b>	<b>Mean</b>	<b>SD</b>	<b>Min.</b>	<b>25th Percentile</b>	<b>Median</b>	<b>75th Percentile</b>	<b>Max</b>
Percent (%) of Tuition and Fee Revenue out of Total Revenue	25	21.4	7.0	15.0	16.9	17.4	22.4	36.6
Percent (%) of State Appropriation Revenue out of Total Revenue	25	30.0	6.7	15.3	29.2	32.1	34.9	37.5

Table 4.5B Descriptive Statistics – University of Arizona (Treatment and Post-treatment Periods)

<b>Variable</b>	<b>N</b>	<b>Treatment Period</b>	<b>Post-Treatment Period</b>		
		<b>2015</b>	<b>2016</b>	<b>2017</b>	<b>2018</b>
Total Operating Costs (outcome variable) (in millions)	1	\$956.56	\$1,077.51	\$1,073.27	\$1,157.84
Full-time Equivalent (FTE) Undergraduate Enrollment	1	30,629	30,842	30,664	30,917
Graduate Enrollment (headcount)	1	9,249	9,264	9,467	9,650
Full-time Faculty	1	1,583	1,591	1,654	1,710
Research Expenditures (in millions)	1	\$476.55	\$452.40	\$457.57	\$497.69
Average Faculty Salary (9-month equated salary)	1	\$92,727	\$94,491	\$97,444	\$98,087
Percent (%) of STEM bachelor's degrees produced out of total conferred	1	31.2	33.0	32.3	34.2
Tuition and Fee Revenue (in millions)	1	\$749.41	\$805.14	\$854.29	\$867.56
State Appropriation Revenue (in millions)	1	\$294.48	\$265.31	\$271.76	\$282.53
Revenue from Private Gifts, Grants, and Contracts (in millions)	1	\$89.98	\$80.89	\$80.06	\$81.75

Variable	N	Treatment Period	Post-Treatment Period		
		2015	2016	2017	2018
Percent (%) of Tuition and Fee Revenue out of Total Revenue	1	36.7	39.5	40.5	40.9
Percent (%) of State Appropriation Revenue out of Total Revenue	1	14.4	13.0	12.9	13.3

### Synthetic University of Arizona

Following the same procedure as the analysis of the UNH, I used the *synth* command in Stata to estimate a control group known as the synthetic control unit by identifying donor units (untreated units) from the donor pool who's predictor variables best resembled the pretreatment characteristics (predictor variables) of the treated unit. Specifically, the synthetic control method assigned a weight ( $w$ ) to each of the units in the donor pool. The weights ranged from zero to one and summed to one. Donor units with weights above zero were selected to be a part of the synthetic control unit.

Table 4.6 shows the composition of the synthetic control unit for the University of Arizona (hereafter referred to as Synthetic University of Arizona or Synthetic UofA). Synthetic UofA is composed of ten universities: University of Georgia, University of California-Berkeley, University of South Carolina-Columbia, Florida International University, University of California-San Diego, Michigan State University, University of Wisconsin-Madison, Virginia Polytechnic Institute and State University, The University of Texas at Austin, and Texas A&M University-College Station. The weighted characteristics (predictor variables) of Synthetic UofA were used to estimate a pretreatment root mean square prediction error (RMSPE) and a post-treatment

counterfactual for each period after RCM was implemented. Below, I describe the pretreatment data analysis and treatment effects.

The University of Georgia possesses the most predictive power (nearly 26%) for operating costs at UofA because the University of Georgia’s pretreatment characteristics most closely resemble those of UofA. This means, for example, that the predictor variables for the University of Georgia will provide the most influence on estimating the pretreatment RMSPE and the post-treatment counterfactual for each period. Below, I describe the pretreatment data analysis and treatment effects.

Table 4.6 Synthetic Control Unit for University of Arizona (Synthetic UofA)

<b>UnitID</b>	<b>Institutions (synthetic controls)</b>	<b>State</b>	<b>Weight (<math>w</math>)</b>
139959	University of Georgia	GA	0.257
110635	University of California-Berkeley	CA	0.168
218663	University of South Carolina-Columbia	SC	0.127
133951	Florida International University	FL	0.11
110680	University of California-San Diego	CA	0.098
171100	Michigan State University	MI	0.094
240444	University of Wisconsin-Madison	WI	0.075
233921	Virginia Polytechnic Institute and State University	VA	0.032
228778	The University of Texas at Austin	TX	0.022
228723	Texas A & M University-College Station	TX	0.017

### **Analysis of Pre-treatment Data**

After the synthetic control unit was estimated, I used the SCM to approximate: (1) the predictor variable values for the synthetic control unit that produced the lowest pretreatment root mean square prediction error (RMSPE) and (2) the weights ( $v_k$ ) of each predictor variable in the analysis. Table 4.7 illustrates the predictor variable values for the University of Arizona and the estimated predictor variable values for Synthetic UofA (i.e., the control group). The predictor variable values for Synthetic UofA were estimated



based on the weights ( $w$ ) from each synthetic unit (i.e., each of the ten universities that are a part of Synthetic UofA). All predictor variables, including the outcomes variable, total operating cost, were specified in the analysis over three different periods: 2000, 2009, and 2014. Consistent with other studies that employ SCM (Barone & Mocetti, 2014; Eren et al., 2016; Jaquette et al., 2018; Liu, 2015), year-specified variables were included in the analysis to produce the lowest possible pretreatment RMSPE. Possessing a low pretreatment RMSPE minimizes the difference between the treated unit and the synthetic control unit. In theory, the pretreatment predictor variables (i.e., pretreatment characteristics) of the University of Arizona and Synthetic UofA two should be nearly identical. This, in turn, increases confidence in the post-treatment counterfactual.

The specified years of 2000, 2009, and 2014 were selected after a series of iterative exercises were conducted. Specifically, I included a variable for all predictor variables in the year preceding the treatment (i.e., 2014). Next, I used the *synth* command in Stata to identify which combination of other year-specified variables, when included in the analysis with variables from the year 2014, would produce the lowest pre-treatment RMSPE. After testing over 20 different combinations of variables across different years, I concluded that variables specified in 2000 and 2009 produced the lowest pre-treatment RMSPE.

The pretreatment RMSPE produced by this set of predictor variables was 17.63. This means that the average difference in total operating costs between the treated unit and the synthetic control unit (Synthetic UofA) in the pre-treatment period is \$17.63 million. This pretreatment RMSPE represents less than four percent of UofA's pre-treatment average total operating costs. Thus, the difference in operating costs between

the treated unit (UofA) and the synthetic control unit (Synthetic UofA) is trivial. This suggests a good pre-treatment fit and increases confidence in the estimated synthetic control unit (i.e., Synthetic UofA).

Table 4.7 illustrates the predictor variable values for the University of Arizona and the estimated predictor variable values for Synthetic UofA (i.e., the control group). Table 4.7 also shows the average predictor variable values of the unweighted donor pool. The donor pool predictor variable values are shown in Table 4.7 to illustrate that the synthetic control unit is a better control group than the unweighted donor pool. For example, by comparing the values of the predictor variables for UofA to the estimated predictor variables of Synthetic UofA and the predictor variables of the unweighted donor pool, it is clear that the Synthetic UofA is a better control group than the unweighted donor pool. For example, the outcome variable for total operating costs in 2000 is \$400.73 million for UofA, \$404.65 million for Synthetic UofA, and \$182.23 million for the unweighted donor pool. It is clear that Synthetic UofA is a more precise control group. Specifically, the unweighted donor pool, if used as the control group for UofA, would produce a poor pre-treatment fit (and post-treatment counterfactual by extension).

Table 4.7 also shows the weights ( $v_k$ ) of each predictor variable in the analysis. Each weight ( $v_k$ ) describes how well each predictor variable predicts the outcome variable (total operating costs). The value of the weights ( $v_k$ ) ranges from zero to one and sum to one. Predictor variables with weights closer to one have higher predictive power than those closer to zero. As shown in Table 4.7, the outcome variables for total operating costs possessed the most predictive power over the pretreatment period. Specifically,

total operating costs from the year 2000 accounted for 0.305 (or 30.5%) of the predictive power. Operating costs from 2009 accounted for 0.199 (or 19.9%) of the predictive power. Finally, operating costs from 2014 (i.e., the year preceding RCM implementation) made up 0.308 (or 30.8%) of the predictive power.

The next strongest predictors were: research expenditures from 2009 (which possessed 2.7% of predictive power); tuition and fee revenue from 2009 (2.6%); tuition and fee revenue from 2014 (2.5%); state appropriations from 2009 (1.4%); research expenditures from 2014 (1.2%); and tuition and fee revenue from 2000 (1.1%). The remaining predictor variables possessed predictive power of less than one percent.

Table 4.7 University of Arizona Pre-treatment Estimates

<b>Predictor Variable</b>	<b>University of Arizona (Treated Unit)</b>	<b>Synthetic University of Arizona (Control Unit)</b>	<b>Donor Pool (n=126)</b>	<b>Predictor Variable Weights (<math>v_k</math>)</b>
Total Operating Cost (USD in millions) (2000)	\$400.73	\$404.65	\$182.23	0.305
Total Operating Cost (USD in millions) (2009)	\$576.43	\$604.75	\$304.02	0.199
Total Operating Cost (USD in millions) (2014)	\$881.36	\$865.98	\$412.73	0.308
Full-time Equivalent (FTE) Undergraduate Enrollment (2000)	23,155	21,558	12,421	0.002
Full-time Equivalent (FTE) Undergraduate Enrollment (2009)	27,215	25,033	14,863	0.006
Full-time Equivalent (FTE) Undergraduate Enrollment (2014)	29,491	27,190	16,120	0.004
Graduate Enrollment (headcount) (2000)	6,944	6,387	3,687	0.001
Graduate Enrollment (headcount) (2009)	8,341	7,643	4,423	0.002

<b>Predictor Variable</b>	<b>University of Arizona (Treated Unit)</b>	<b>Synthetic University of Arizona (Control Unit)</b>	<b>Donor Pool (n=126)</b>	<b>Predictor Variable Weights (<math>v_k</math>)</b>
Graduate Enrollment (headcount) (2014)	8,951	8,984	4,959	0.004
Percent (%) of STEM bachelor's degrees produced out of total (2000)	26.4	28.3	26.6	0.000
Percent (%) of STEM bachelor's degrees produced out of total (2009)	28.9	27.9	25.7	0.001
Percent (%) of STEM bachelor's degrees produced out of total (2014)	31.2	33.2	29.7	0.000
Full-time Faculty (2000)	1,348	1,384	722	0.005
Full-time Faculty (2009)	1,593	1,538	872	0.004
Full-time Faculty (2014)	1,561	1,676	913	0.002
Average Faculty Salary (9-month equated salary) (2000)	\$67,451	\$70,858	\$58,356	0.001
Average Faculty Salary (9-month equated salary) (2009)	\$87,187	\$92,385	\$76,615	0.003
Average Faculty Salary (9-month equated salary) (2014)	\$92,880	\$99,577	\$80,692	0.001
Percent (%) of State Appropriation Revenue out of Total Revenue (2000)	34.2	36.3	37.0	0.000
Percent (%) of State Appropriation Revenue out of Total Revenue (2009)	25.5	25.2	27.9	0.001
Percent (%) of State Appropriation Revenue out of Total Revenue (2014)	15.7	17.7	22.5	0.000
Percent (%) of Tuition and Fee Revenue out of Total Revenue (2000)	17.1	17.4	21.5	0.001

<b>Predictor Variable</b>	<b>University of Arizona (Treated Unit)</b>	<b>Synthetic University of Arizona (Control Unit)</b>	<b>Donor Pool (n=126)</b>	<b>Predictor Variable Weights (<math>v_k</math>)</b>
Percent (%) of Tuition and Fee Revenue out of Total Revenue (2009)	25.9	27.2	29.8	0.004
Percent (%) of Tuition and Fee Revenue out of Total Revenue (2014)	36.6	34.6	34.9	0.001
Research Expenditures (USD in millions) (2000)	\$235.74	\$231.00	\$64.14	0.007
Research Expenditures (USD in millions) (2009)	\$385.47	\$344.42	\$110.36	0.027
Research Expenditures (USD in millions) (2014)	\$451.27	\$460.12	\$139.90	0.012
Revenue from Private Gifts, Grants, and Contracts (USD in millions) (2000)	\$75.61	\$82.07	\$24.76	0.001
Revenue from Private Gifts, Grants, and Contracts (USD in millions) (2009)	\$78.16	\$73.69	\$21.06	0.002
Revenue from Private Gifts, Grants, and Contracts (USD in millions) (2014)	\$78.29	\$95.69	\$30.35	0.003
State Appropriation Revenue (USD in millions) (2000)	\$320.91	\$328.77	\$134.08	0.009
State Appropriation Revenue (USD in millions) (2009)	\$371.49	\$344.61	\$169.08	0.014
State Appropriation Revenue (USD in millions) (2014)	\$287.49	\$303.55	\$165.30	0.008
Tuition and Fee Revenue (USD in millions) (2000)	\$160.65	\$162.14	\$73.65	0.011
Tuition and Fee Revenue (USD in millions) (2009)	\$377.35	\$369.23	\$173.37	0.026
Tuition and Fee Revenue (USD in millions) (2014)	\$670.32	\$599.11	\$257.92	0.025

## Treatment Effects

The University of Arizona implemented RCM in the year 2015. Due to the availability of existing data, treatment effects on the impact of RCM on total operating costs at UofA were assessed each year for three years after RCM had been implemented. Figure 4.2 was generated using the *synth* command in Stata. Figure 4.2 illustrates the total operating costs at UofA and the estimated total operating costs at Synthetic UofA. After RCM was implemented in the year 2015, total operating costs at UofA increased. The synthetic control analysis was used to determine whether the increase in total operating costs at UofA inferred causality as a result of RCM implementation. Specifically, the synthetic control method estimated a post-treatment counterfactual (i.e., what would have occurred at UofA in the absence of RCM) for each year of the post-treatment period. Synthetic UofA in the post-treatment period represents what would have occurred at UofA if RCM had not been implemented. As shown in Figure 4.2, the estimated total operating costs at Synthetic UofA increased each year after RCM had been implemented, however, the estimates did not exceed the total operating costs at UofA. This suggests that in the absence of RCM, total operating costs at UofA would have been lower.

To determine whether RCM had a significant causal effect on total operating costs, treatment effects of RCM's were estimated using the *synth\_runner* command in Stata. Treatment effects are the difference between the actual total operating costs at UofA and the estimated total operating costs at Synthetic UofA. As illustrated in Table 4.8, the magnitude of the treatment effects of RCM on total operating costs at UofA ranged from \$52.79 million to \$108.51 million over the three-year post-treatment period.

For example, after the first year of RCM implementation, the results inferred causality that RCM increased total operating costs by \$108.51 million more than if RCM had not been implemented. However, the magnitude of the treatment effects declined after the first year. Specifically, in 2017, the results suggest that RCM increased operating costs by \$52.79 million more than it would have been in the absence of RCM. This shows a decline in the magnitude of the treatment effect between 2016 and 2017. Additionally, in 2018, the results indicate that RCM increased total operating costs by \$52.14 million more than costs would have been if RCM had not been implemented. These results suggest overall that RCM increased total operating costs at UofA. To assess the significance and robustness of the results, a series of placebo tests and sensitivity analyses were conducted. The results of the placebo tests and leave-one-out test are discussed next.

Figure 2. Graph of Treatment Effects of RCM’s Impact on Operating Cost at University of Arizona

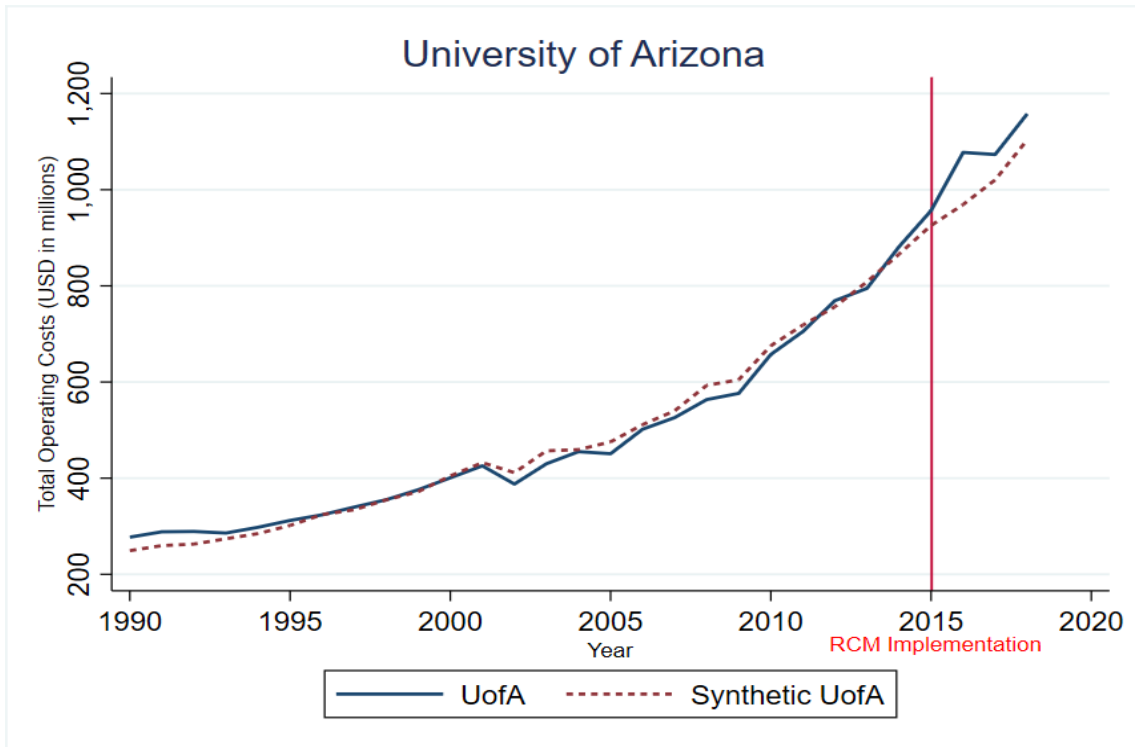


Table 4.8 Treatment Effects of RCM's Impact on Operating Cost at University of Arizona

Total Operating Costs (USD in millions)					
Post-Treatment Period	Year	UofA	Synthetic UofA	Treatment Effect (UofA - Synthetic UofA)	P-Value
1	2016	\$1,077.51	\$969.00	\$108.51	0.063
2	2017	\$1,073.27	\$1,020.48	\$52.79	0.190
3	2018	\$1,157.84	\$1,103.70	\$54.14	0.238

### Placebo Tests and Inference

A series of in-place (across-unit) placebo tests were conducted to obtain the *p-values* for each post-treatment period. Specifically, the *synth\_runner* command artificially reassigned the RCM "treatment" to each of the 126 units in the donor pool and calculated a "placebo" effect for each donor unit across each post-treatment period. This means that 126 different placebo effects were estimated across three years. Thereafter, the *synth\_runner* command estimated a cumulative distribution of "placebo" effects for each post-treatment year. Next, the analysis calculated the probability of obtaining a placebo effect that was greater than or equal to the actual treatment effect for each year.

The results of these calculations are illustrated in Table 4.8. Only one *p-value* (i.e., from the first year of RCM implementation) reached a level of significance to conclude that RCM had a significant causal effect on total operating costs ( $p \leq 0.10$ ). Specifically, after the first year of RCM implementation, the estimated *p-value* is 0.063. This means that there is a 6.3% probability that RCM's impact on total operating costs occurred by chance. Put another way, this *p-value* suggests that there is a 93.7% probability that the treatment effect of RCM *did not* occur by chance. These results indicate that RCM *caused* total operating costs to be \$108.51 million higher than costs would have been if RCM had not been implemented.



The *p-values* for the second and third years after RCM implementation suggest that RCM positively impacted total operating costs but not enough to infer causality. Specifically, the *p-value* for the second year after RCM implementation indicates that there is a 19% probability that the treatment effect of RCM occurred by chance. Additionally, the *p-value* for period three suggests that there is a 23.8% probability that the treatment effect of RCM's impact on cost occurred by chance. Both *p-values* are above the 10% threshold needed to conclude that RCM *caused* total operating costs to be higher than they would have been in the absence of RCM. Put another way, the results indicate that RCM impacted total operating costs. However, for these two years, we cannot conclude that RCM *caused* total operating costs to be higher than they would have been if RCM had not been implemented. Sensitivity analyses were conducted next to discern the robustness of the results.

### **Leave-One-Out Test**

The leave-one-out test was conducted to investigate the robustness of the results. To conduct the leave-one-out test, I utilized the same strategy as I did with UNH by removing the most influential control (i.e., university) from the synthetic control unit. Specifically, I removed the University of Georgia from Synthetic UofA and used the *synth* and *synth\_runner* commands in Stata to rerun the analysis. As shown in Table 4.6, the University of Georgia possessed nearly 26% of explanatory power for UofA.

The leave-one-out analysis revealed that the main results of the study on UofA were robust after the University of Georgia was removed from Synthetic UofA. Specifically, after the University of Georgia was removed, the pretreatment estimation of the treated unit was not severely weakened. For example, as illustrated in Table B5 in

Appendix B, a comparison of the pretreatment estimates of UofA, Synthetic UofA (with University of Georgia), and Synthetic UofA (without University of Georgia) illustrate that Synthetic UofA (without University of Georgia) provided an adequate pretreatment estimation of UofA. This is underscored by Figure B2 in Appendix B. Specifically, the difference in total operating costs between UofA and Synthetic UofA (with the University of Georgia removed) is not substantially different from Figure 2 (without the University of Georgia removed). More specifically, the pretreatment RMSPE, which is a measure of the goodness of fit, increased from \$17.6 million (without the University of Georgia removed) to \$19.6 million (with the University of Georgia removed). Because \$19.6 million represents about four percent of the average pretreatment operating costs at UofA, it suggests a good pretreatment fit – that is, the new Synthetic UofA (with the University of Georgia removed) is an appropriate pretreatment estimation of UofA. Therefore, confidence is strengthened in the estimations of the treatment effects for both the leave-one-out test as well as the main SCM analysis.

The treatment effects that were estimated by the leave-one-out test are illustrated in Table B6 in Appendix B. Similar to the main findings (which include the University of Georgia as a part of Synthetic UofA), the treatment effects estimated after the leave-one-out test suggest that RCM positively impacted total operating costs. However, the *p-values* estimated after the leave-one-out test are all higher than the 10% threshold needed to infer causality. Specifically, after the first year of RCM implementation, the results show that total operating costs would have been \$156.89 higher than if RCM had not been implemented. The *p-value* is 0.556. Additionally, after the second year of RCM, the estimated treatment effects indicate that RCM positively impacted total operating costs to

be \$115.76 greater than they would have been in the absence of RCM. The *p-value* is 0.778. These results, although not the same as the main SCM results (which include the University of Georgia as part of Synthetic UofA), increase confidence in the main findings. Specifically, the estimated treatment effects for the first and second post-treatment periods assessed as part of the leave-one-out test show that RCM impacted total operating costs to increase (see Table B6 in Appendix B). However, the *p-values* for periods one and two are below the 10% threshold to conclude that RCM had a causal effect on total operating costs.

The estimated treatment effect for year three as part of the leave-one-out test departs from the results of the main findings (which include the University of Georgia as part of Synthetic UofA). Specifically, the treatment effect for year three assessed as part of the leave-one-out test indicates that RCM negatively impacted total operating costs—suggesting that total operating costs would have been nearly \$40.3 million lower than if RCM had not been implemented. The *p-value* is 1, which suggests that RCM did not impact total operating costs. As a consequence, confidence in the main finding for year three is diminished.

The overall results of the leave-one-out test suggest that the University of Georgia is an influential control unit; however, the exclusion of the University of Georgia from the analysis does not significantly change the treatment effects for the first two years of RCM implementation. However, the treatment effects of the third year should be interpreted with caution due to the differences between the treatment effects of the leave-one-out test and the main SCM analysis. A summary of these findings will be discussed at the end of the chapter.

## Summary of Results

This study examined the impact of RCM on costs at two public research universities in the United States: the University of New Hampshire and the University of Arizona. Using the synthetic control method, this study elucidates several key findings worth noting. First, with regard to the University of New Hampshire, which implemented RCM in the year 2000, the results of the synthetic control analysis reveal varying levels of evidence that RCM impacted total operating costs between 2002 and 2005. However, the estimated *p-values* across the post-treatment period indicate that RCM may have impacted costs but not enough to infer causality. Additionally, the results of the sensitivity analysis show that the findings should be interpreted with caution.

Between 2002 and 2005, the results suggest that RCM positively impacted total operating costs (i.e., costs were higher than they would have been if RCM had not been implemented). Indeed, the magnitude of the effects range from \$15.69 million to \$28.17 million between 2002 and 2005. However, after a series of placebo tests, the results with the greatest confidence are from 2002 and 2003. Specifically, in these years, RCM positively impacted total operating costs to be \$19.15 million (2002) and \$28.17 million (2003) higher than they would have been if RCM had not been implemented. However, confidence in these findings was severely weakened after placebo tests were conducted. The lowest *p-value* was 0.212 in 2003 and the highest was 0.939 in 2001. Because each of these *p-values* is not at or below 10%, it indicates that RCM did not have a significant causal effect on total operating costs at UNH.

With regard to the University of Arizona, which implemented RCM in 2015, the results show that RCM *caused* total operating costs to increase after the first year of

implementation. Specifically, total operating costs were \$108.51 million higher than they would have been if RCM had not been implemented. A series of placebo tests confirmed with high confidence that this result did not occur by chance ( $p\text{-value} = 0.063$ ).

Additionally, the results reveal that RCM positively impacted costs in the second and third years after RCM had been implemented. However, after a series of placebo tests, the  $p\text{-values}$  did not conclude that RCM had a causal effect on total operating costs ( $p \leq 0.10$ ).

## **Chapter 5: Discussion and Recommendations**

### **Introduction**

This study examined the impact of Responsibility Center Management (RCM) on costs at two public research universities in the United States: the University of New Hampshire (UNH) and the University of Arizona (UofA). The implementation of RCM at each university in this study is considered the *treatment*. The UNH implemented RCM in the year 2000 and the UofA implemented RCM in 2015. This study used two institution-level panel datasets (one for each university to account for the different sample periods) and employed the synthetic control method (SCM) to conduct the analysis. The dataset for the UNH contained data on 133 public research universities across 16 years (1990-2005). The dataset for the UofA contained data on 127 public research universities across 29 years (1990-2018). The datasets contain an outcome variable and several predictor variables. The outcome variable is total operating costs and is defined as the sum of expenditures on academic administration, institutional administration, instruction, and student services. The predictor variables in this study were adopted from previous higher education cost research and were used in this study to estimate the synthetic versions of UNH and UofA – specifically, to predict what total operating costs would have been at UNH and UofA if RCM had not been implemented. These predictor variables include full-time equivalent undergraduate enrollment, graduate headcount, the number of full-time faculty, research expenditures, the average faculty salary, the proportion of students graduating with degrees in science, technology, engineering, and mathematics (STEM) out of the total number of graduates, tuition and fee revenue, state appropriations, private

gifts, grants, and contracts, the proportion of tuition and fee revenue out of total revenue, and the proportion of state appropriation revenue out of total revenue.

The results of the study, as presented in the previous chapter, show that both the UNH and UofA increased total operating costs after RCM was implemented. With regard to UNH, the results indicate that RCM positively impacted total operating costs between 2001 and 2005. However, after a series of placebo tests, the results indicate that RCM positively impacted costs but not enough to infer causality. With regard to the UofA, the results indicate that RCM *caused* total operating costs to increase in the first year of implementation. However, after a series of placebo tests, the results indicate that RCM positively impacted total operating costs in years two and three but not enough to infer causality.

The purpose of this chapter is severalfold. First, this chapter discusses the findings with respect to each university in the study. Next, the chapter discusses the significance of the findings in the context of the extant literature. Third, this chapter describes how the findings of this study contribute to research and practice. Thereafter, this chapter identifies and explains the implications for policy, research, and theory. Finally, the chapter concludes with recommendations to guide future research.

## **Discussion**

### **University of New Hampshire**

Prior to the implementation of RCM at UNH in the year 2000, the institution experienced changes with regard to total operating costs. Indeed, between 1980 and 1999, total operating costs increased by 71% (after adjusting for inflation in 1999 dollars). After

an 18-month exploration study was conducted by UNH's RCM Steering Committee, the then-President Joan Leitzel furnished a memo on January 14, 2000 to the campus citing five reasons for moving the campus to RCM. Among them, she noted, "[t]here will be stronger incentives for cost effectiveness and revenue generation" (Joan Leitzel, personal communication, January 14, 2000). However, as shown in the previous chapter of this study (*Chapter 4: Results*), total operating costs rose in current dollars (i.e., not adjusted for inflation) each year after RCM had been implemented. Specifically, after the first year of RCM implementation in the year 2000, operating costs rose from \$120.09 million to \$125.41 million and continued to rise thereafter.

Moreover, after employing the synthetic control method to estimate the treatment effects of RCM's impact, the results of this study revealed that the magnitude of the effects of RCM on total operating costs at UNH ranged from \$600,000 to \$28.17 million and differed across each year between 2001 and 2005. After a series of placebo tests were conducted, the analysis revealed that RCM did not have a significant causal effect on total operating costs — specifically, the estimated *p-values* across the study period were not low enough to infer causality ( $p \leq 0.10$ ).

As illustrated in the previous chapter (*Chapter Four: Results*), the estimated treatment effect of RCM on total operating costs was \$600,000 after the first year of RCM implementation. The magnitude of the treatment effects increased between the first and third years following the implementation of RCM. Specifically, after the second year in which RCM was implemented, the magnitude of the treatment effect of RCM was \$19.15 million. This suggests that total operating costs were \$19.15 million higher. Similarly, the magnitude of the treatment effect of RCM on total operating costs



increased in the third year following RCM implementation. More specifically, after the third year of RCM implementation, the results indicate that RCM positively impacted total operating costs to be \$28.17 million higher. However, the magnitude of the treatment effect of RCM on total operating costs decreased thereafter. For example, the magnitude of the treatment effect decreased from an additional \$28.15 million in 2003 (year three) to an additional \$16.19 million in 2004 (year four). The magnitude of the treatment effect decreased from an additional \$16.19 million in 2004 (year four) to an additional \$15.69 million in 2005 (year five). The positive effect of RCM on total operating costs declined over the five-year post-treatment period.

These findings, although they do not provide causal evidence that RCM increased total operating costs at UNH, are important for several reasons. First, these findings indicate that RCM at UNH did not achieve the goal of decreasing costs as was originally intended. Second, the findings show that leaders at UNH should have evaluated RCM's impact on costs in the first internal review of RCM in 2006. Specifically, since the implementation of RCM at UNH in the year 2000, the UNH's RCM model and allocation formulae have been reviewed and modified at least three times: in 2006, 2009, and 2015. The 2006 internal review (which considered the first five years of RCM) focused on curriculum, research/outreach, and administration under RCM – not operating costs (UNH, 2006). The other internal reviews also did not explicitly examine the extent to which RCM impacted operating costs either (UNH, 2009; 2015). If university leaders had reviewed RCM's impact on total operating costs in the first internal review, perhaps then they would have been able to incorporate changes to the RCM model and allocation formulae beginning in the 2006 fiscal year. More research regarding the changes to

UNH's RCM model would be necessary to discern if, and to what extent, total operating costs changed as a result of the modifications to the model.

Third, the results are important because they illustrate that the magnitude of the treatment trended downward after the fourth year. Specifically, the magnitude of the treatment effects increased between the first and third years and then decreased thereafter. This suggests that the initial costs of operating RCM were perhaps higher at the outset of the implementation of RCM compared to after RCM had been in place for three years. This may indicate that university leaders became more accustomed to the new budget model over time. Additionally, the decrease in the magnitude of the treatment effect may suggest that the embedded incentives in RCM with regard to costs (i.e., the decentralization of budget authority and the carry forward principle) were better utilized over time. Despite a decrease in the magnitude of the effects of RCM on total operating costs by year four, total operating were still higher than they would have been if RCM had not been implemented.

Finally, despite the lack of evidence to conclude that RCM had a significant causal impact on total operating costs at UNH, the results still call into question the worthwhileness of the implementation of RCM at UNH. As noted previously, the university undertook an 18-month study to examine the feasibility and need for implementing RCM, having realized challenges with operating costs leading up to the implementation.

Because the analysis did not conclude that RCM had a significant causal impact on total operating costs at UNH, there are a few alternative explanations that may have contributed to the increase in operating costs over the post-treatment period. For example,

over the post-treatment period (between 2000 and 2005): a) the number of full-time faculty members grew by nearly 11%; b) the average faculty salary rose by more than 34% (in current dollars); c) research expenditures increased in current dollars from \$64.49 million to \$89.02 million (i.e., a 38% increase); and d) the amount of tuition and fee revenue collected by UNH increased by approximately 28% (in current dollars).

Previous scholarship on higher education cost has conclusively shown positive relationships between costs and the number of full-time faculty, average faculty salary, research expenditures, and revenue (deGroot et al., 1991; Leslie et al., 2012; Koshal & Koshal, 1999; Robst, 2001; Titus et al., 2017).

### **University of Arizona**

The University of Arizona experienced financial changes prior to the implementation of RCM in 2015. Between 2003 and 2014 (the year before RCM was implemented), UofA experienced a 34% decline in state appropriations (after adjusting for inflation in 2014 dollars) and total costs rose by nearly 30%. In the fall of 2012, the UofA provost convened a steering committee to investigate the feasibility of implementing RCM. After more than two years of feasibility testing, RCM was implemented to increase transparency around revenues and costs and to grow revenue while also becoming more cost effective in the wake of significant financial changes at the university (University of Arizona, 2017). However, as shown in the previous chapter of this study (*Chapter 4: Results*) total operating costs rose in current dollars (i.e., not adjusted for inflation) after RCM had been implemented and each year thereafter.

Specifically, operating costs rose from \$956.56 million in 2015 to approximately \$1.08

billion in 2016. In 2017 and 2018, total operating costs were about \$1.07 billion and \$1.16 billion, respectively.

After employing the synthetic control method to estimate the treatment effects of RCM's impact, the results revealed that the magnitude of the effects of RCM on total operating costs at UofA ranged from \$52.79 million to \$108.51 million between 2016 and 2018. Specifically, after the first year of RCM implementation, the results show that RCM *caused* total operating costs to be \$108.51 million higher than if RCM had not been implemented ( $p \leq 0.10$ ). However, after a series of placebo tests on the remaining years of the post-treatment period, the results did not show that RCM had a significant causal effect on total operating costs.

Additionally, the magnitude of the treatment effects declined after the first year. For example, after the second year, the magnitude of the treatment effect of RCM was \$52.79 million. This suggests that RCM positively impacted total operating costs to be \$52.79 million higher. It also illustrates a steep decline in the magnitude of the treatment effect between the first and second years. Similarly, after the third year following RCM implementation, the magnitude of the treatment effect was \$54.14 million. The magnitude of treatment effect for the third year was again lower than the first year and not much different than the second year of RCM implementation.

As similarly described in the UNH case, the results of this study with regard to UofA are important. First, these findings indicate that RCM at UofA did not achieve the goal of controlling costs as was originally intended. Second, the results illustrate that the magnitude of the treatment effect of RCM on total operating costs declined over the post-treatment period. This may also suggest that the initial costs of implementing and

operating RCM were higher compared to the costs of operating RCM over time. Additionally, this may indicate that leaders at UofA became more experienced with RCM and better utilized the embedded incentives in RCM to curb costs over time compared to the first year after implementing RCM. However, despite a decline in the magnitude of the treatment effect of RCM, total operating costs were higher than they would have been if RCM had not been implemented. As a consequence, these results call into question the worthwhileness of the implementation of RCM at UofA. As noted above, the UofA conducted a multi-year study to develop and examine the feasibility of implementing RCM. Specifically, several committees were formed to build the RCM guiding principles, develop the budgetary infrastructure (i.e., aligning enterprise and data systems), and test the RCM model (University of Arizona, 2017). The UofA conducted a three-year internal review of RCM in 2018. However, no report has been furnished publicly to demonstrate the extent of the review or any changes that were recommended in response to their findings. Changes in senior leadership may have caused changes in the RCM model during the post-treatment period, and perhaps may have caused delays in the availability of the report. Additional research is necessary to understand if changes in leadership may have impacted the implementation of RCM in terms of emphasis; more so on increasing revenue than on decreasing costs at UofA.

In addition to RCM's impact on total operating costs at UofA, there are a couple of alternative explanations that may have contributed to the increase in operating costs over the post-treatment period. For example, the stated goals for implementing RCM at the UofA – specifically to grow revenue and control costs – were perhaps in conflict with one another. According to Bowen's (1980) RTC, an increase in revenue corresponds with

an increase in costs. The largest source of revenue at UofA (i.e., tuition and fee revenue) rose in current dollars from \$670.32 million in 2014 (the year prior to RCM implementation) to \$805.14 million in 2016 (the first year following RCM implementation). The increase in tuition and fee revenue (by more than \$135 million) between 2014 and 2016 may have impacted costs as well. Additionally, from an external perspective, the Arizona Board of Regents (ABOR) implemented an aggressive strategic plan for public universities in the state of Arizona over the post-treatment period of RCM at UofA. This strategic plan calls for Arizona universities to be entrepreneurial, accountable, and collaborative in the achievement of the statewide goals tied to several metrics that ranged from enrollment, retention, and degree production to research activity and public service (ABOR, n.d.). However, as mentioned above, state appropriations to the UofA have decreased considerably over the last decade. By 2018, state appropriations as a share of total revenue at UofA represented 13.3%, whereas revenue from tuition and fees represented more than 40% of total revenue. With the continuous decline in state support to UofA, it is possible that items listed in ABOR's strategic plan were not specifically tied to additional funding. This would, in turn, lead to higher spending over the post-treatment period, which conflicts with the goal of implementing RCM (i.e., to control costs). However, further research is necessary to understand the extent to which the ABOR's strategic plan impacted costs at UofA.

### **Discussion of the Findings in the Context of Extant Literature**

Prior to this study, previous empirical research from the RCM literature and the higher education cost literature had not considered RCM with regard to its effect on costs. Thus, the results of this study cannot be directly compared with prior work. From

the RCM literature, researchers (Jaquette et al., 2018) noted the need to investigate RCM's effect on costs due to the lack of empirical research and the abundance of non-empirical publications that bolster RCM's effects without appropriate substantiation (e.g., Attis et al., 2016; Curry et al., 2013; Strauss & Curry, 2002). To explain RCM's potential effect on costs, Jaquette and associates (2018) hypothesized that RCM may cause costs to increase due to the administrative requirements for operating RCM. However, this was not the focus of their research.

With regard to the higher education costs literature, there is no empirical study that examines RCM's impact on costs with which to compare the results of this study. Despite the lack of research on RCM and costs, scholars have noted that a study was warranted because many public research universities adopted RCM as a means to control costs (Chestlock, 2016; Titus et al., 2017; Toutkoushian, 1999). As a consequence, the findings from this study with respect to RCM's impact cannot be directly compared with previous research.

### **Contributions to Research**

Because no previous study investigated the impact of RCM on costs, this study makes at least three distinct contributions to the literature. First, this study is the first to bridge the gap between the RCM literature and the higher education cost literature by providing empirical insight regarding RCM's effect on total operating costs. Second, this study contributes to the use of theory in the RCM literature because it incorporates two theoretical frameworks to guide the research question: the principal-agent theory (PAT) and Bowen's (1980) revenue theory of cost (RTC). Only two previous studies (Cekic, 2010; Jaquette et al., 2018) from the RCM literature were theoretically grounded. Cekic

(2010) used Bolman and Deal's (2003) four frames of organizational culture (i.e., structural/rational, human resources, political, and symbolic) to explain how faculty and administrators interacted with the RCM budgeting and planning processes. Jaquette et. al (2018) incorporated principal-agent theory to explain how the principal-agent relationship between central administration (i.e., the principal) and deans (i.e., the agents) within RCM would impact tuition revenue.

This study used PAT to explain RCM's impact on costs by illustrating the principal-agent relationship between central administration (the principal) and deans (the agents). Specifically, in this study, the implementation of RCM (i.e., the treatment) served as the contract within the PAT framework that bounded the principal-agent relationship. RCM (i.e., the treatment and contract), in turn, allowed central administration (the principal) to incent cost control among deans (the agents). Based on the results of this study – specifically, the positive impact of RCM on total operating costs at both universities in the study – the embedded incentives within RCM around cost control (i.e., the carry forward principle and devolution of budget authority requiring deans to finance the full costs of their respective units) were perhaps ineffective. Indeed, the results suggest that there may have been misaligned goals between the principal and the agents at both universities in the study, due to the increase in total operating costs. The misalignment of goals has been described by scholars (Kivisto, 2005, 2008; Lane et al., 2008) as shirking behavior. This may mean, for example, that deans (the agents) at UNH and UofA acted upon their own self-interests (and the interests of their respective academic units) by increasing operating costs despite central administrations' intent to control costs. However, because this study did not use academic-unit level data nor did it



interview deans, it is difficult to discern the extent to which there was a misalignment in the goals of the principal (central administration) with the agents (deans). For this reason, future research that incorporates academic-unit level data and interviews is necessary to properly employ PAT as a theoretical framework.

The use of PAT was helpful in identifying other principal-agent relationships that may have also contributed to higher spending, specifically at the UofA. For example, as described above, the ABOR implemented an aggressive strategic plan for public universities in the state of Arizona over the post-treatment period of RCM at UofA. This introduced another principal-agent relationship into the study, specifically between ABOR (the principal) and UofA (the agent). In this case, the strategic plan became the contract that bound the ABOR and the UofA. However, as a consequence of decreased state funding to the UofA over the last decade, the goals of ABOR and the UofA's implementation of RCM (i.e., to control costs) were perhaps in conflict. Specifically, many of the items in ABOR's strategic plan were not tied to increased state appropriations to the UofA. This suggests that spending related to the achievement of the items in ABOR's strategic plan would come from the UofA coffers. This, in turn, would lead to higher spending at UofA over the post-treatment period.

With regard to Bowen's (1980) RTC, this study incorporated university revenue data to theoretically frame the impact of revenues on costs. Bowen (1980) and many scholars (e.g., Brinkman, 1990; Clotfelter, 1996; Martin, 2011; Winston, 1999) have argued that colleges and universities are not cost minimizers, and have instead suggested that colleges and universities seek to maximize their prestige and influence. Indeed, these

scholars contend that colleges and universities, as a consequence of maximizing their prestige and influence, increase costs substantially.

This study provides some support for RTC as it relates to the notion that colleges and universities are not cost minimizers. For example, based on the results of this study – specifically the increase in total operating costs caused by RCM at UNH – there is evidence to suggest that administrators at UNH increased spending after implementing RCM in order to maximize their prestige, excellence, and influence. For example, as noted earlier in this chapter, over the post-treatment period (between 2000 and 2005) at the UNH: a) the number of full-time faculty members grew by nearly 11%; b) the average faculty salary rose by more than 34% (in current dollars); c) research expenditures increased in current dollars from \$64.49 million to \$89.02 million (i.e., a 38% increase); and d) the amount of tuition and fee revenue collected by UNH increased by approximately 28% (in current dollars). This could suggest that central administrators and deans at UNH individually or collectively increased costs by spending on activities and items that contributed to the prestige of the institution or each of their respective colleges and schools. This behavior, in turn, would have been at odds with the goal of implementing RCM (i.e., to control costs).

Additionally, this study contributes to the literature because it overcame several methodological limitations of previous research by employing SCM to assess the causal effects of RCM's impact. As described in *Chapter 2: Literature Review*, previous literature on RCM is limited methodologically for several reasons: first, due to the overuse of qualitative methods (Cekic, 2010; Courant & Knepp, 2002; Deering & Sá, 2014, 2018; Gros Louis & Thompson, 2002; Lang, 2002); second, due to the use of

qualitative methods to describe the quantitative effects of RCM (Lang, 2002); and third, due to the use of inappropriate quantitative techniques to reveal RCM's impact on quantifiable outcomes (Hearn et al., 2006; McBride et al., 2000; Rutherford & Rabovsky, 2017). As a consequence, our empirical knowledge of RCM has remained relatively limited.

Employing SCM in this study addressed each of the previously mentioned methodological limitations of prior research. First, the use of SCM contributes to the limited and mostly qualitative extant body of scholarship on RCM. Moreover, this study is one of few (e.g., Bonander et al., 2016; Hinrichs, 2012; Liu, 2015; Jaquette et al., 2018) that have employed SCM in the higher education literature domain. Second, the use of SCM in this study did not rely on qualitative methods to describe the quantitative effects of RCM. For example, in a previously discussed qualitative case study on the University of Toronto-Scarborough's (UTS) experience with RCM, Lang (2002) noted that UTS had accumulated a \$5.5 million debt two years after RCM had been fully implemented. However, the scholar did not conduct a quantitative or quasi-experimental analysis to attribute the \$5.5 million debt to RCM. The use of SCM would have been more appropriate to make such a claim regarding UTS's case.

Furthermore, the use of SCM in this study permitted the analysis of if, and to what extent, total operating costs were different than they would have been if RCM was not implemented at UNH and UofA. For example, Hearn et al. (2006) used descriptive analysis to investigate the extent to which RCM impacted student enrollment and the number of credit hours taught across the colleges at the University of Minnesota-Twin Cities. The researchers did not employ a causal or quasi-experimental technique to

appropriately capture what would have occurred with regard to enrollment and the number of credit hours if RCM had not been implemented. Similarly, Rutherford et. al. (2017) employed regression analysis to examine RCM's impact on degree production and graduation rates. However, the scholars did not develop a counterfactual to describe if, and to what extent, graduation rates or degree production might have been different if RCM had not been implemented. In both cases (e.g., Hearn et al., 2006 and Rutherford & Rabovsky, 2017) SCM would have been a more appropriate analytic technique from which to draw conclusions.

The synthetic control method was the most appropriate quantitative technique to address the research question in this study for the reasons stated above. Implications and recommendations for future research regarding the use of SCM for studies on RCM will be discussed in the sections that follow in this chapter.

### **Contributions to Practice**

In addition to research contributions, this study contributes to practice. Prior to this study, no such research existed regarding RCM's impact on costs, and several pro-RCM publications (Curry et al., 2013; Hanover Research, 2008; Strauss & Curry, 2002; Whalen, 1991) relied heavily on descriptive statistics and anecdotal evidence to make claims about RCM's utility. The results of this study – specifically that RCM impacts total operating costs – balance previous anecdotal claims by providing empirical insight on RCM at UNH and UofA to guide future decision-making. More broadly, this study provides insight regarding RCM's effect on total operating costs using two examples (i.e., UNH and UofA) to public policymakers and university administrators that may be considering RCM. Each of these cases (i.e., UNH and UofA) can be further studied by

policymakers and university administrators to provoke discussion about RCM's utility with regard to costs. This is especially important given the financial changes in higher education described in *Chapter 1: Introduction* (e.g., declining state support, escalating costs, and rising tuition prices), as well as the recent attention and adoption of RCM as a strategy to minimize costs (among other goals).

### **Implications**

This study has implications for policy, research, and theory. With regard to policy, the results for UNH show that the first five years of RCM had the opposite effect of what was intended by university leaders with regard to costs. As noted above, the UNH formally reviewed its RCM model internally three times: in 2006, 2009, and 2015. However, none of the internal reviews considered operating costs. As a consequence, the findings from this study imply that university leaders at UNH should have enacted policies that better incentivized cost control. This could have entailed, for example, a review and modification of the RCM funding formulae and cost allocation policies to incentivize compliance for cost control among deans and other responsibility center leaders. There is no mention in the internal reviews (i.e., UNH, 2006; 2009; 2015) that modifications to UNH's allocation formulas explicitly considered costs as the RCM model evolved.

This policy implication applies similarly to the UofA. Specifically, the findings from this study suggest that RCM positively impacted total operating costs, despite university leaders' intentions to harness costs using RCM, among other goals. Only one internal review of RCM has been conducted at the UofA since its implementation in

2015. However, we cannot discern if costs were considered in the internal review of RCM because the report is not publicly available. The findings from this study suggest that university leaders at UofA should consider reevaluating existing incentives for cost control to perhaps increase compliance. This could entail a review and modification of the current funding and cost allocation policies.

Secondly, with regard to policy, university leaders should be aware that time and experience with RCM may affect its impact with regard to total operating costs. Specifically, the results of this study show that the magnitude of the treatment effects of RCM on total operating costs can diminish over time. Specifically, as it relates to UNH, the magnitude of the treatment effects increased initially and decreased by the fourth year. Moreover, regarding the UofA, the magnitude of the treatment effects decreased by the second year. Although in both cases, total operating costs were higher than they would have been if RCM had not been implemented, the decline in the magnitude of the treatment effect warrants additional research.

Lastly, regarding policy, the results of this study could be used to help university leaders at UNH and UofA assess whether the implementation of RCM was worthwhile by balancing their intent to control costs with other motivations for adopting RCM. Including UNH and UofA, college presidents, provosts, and senior administrators at other institutions should closely examine their respective institutions' contexts to determine which motivations are most important for implementing RCM (e.g., to generate additional revenue and to create more flexibility in the budget process). Costs may not be the best impetus for implementing RCM compared to other motivations.

With regard to research, there are several implications worth noting. First, this study used institution-level data to conduct the analysis. While this level of data and analysis adequately addressed the research question regarding RCM's impact on total operating costs, the disaggregation of total operating costs into its components (i.e., expenses on instruction, administration, and student services) would have provided additional details regarding which expenses were most impacted by RCM. For example, after the first year of RCM at the UofA, total operating costs were \$108.51 million higher than if RCM had not been implemented. However, because the components of total operating costs are not disaggregated, it is unclear on which expenses among them (i.e., expenses on instruction, administration, and student services) were most affected. Future research investigating RCM's impact on higher education costs should consider multiple outcome variables in this regard. This implication for research could, in turn, provide university leaders and policymakers with additional evidence to drive better recommendations.

Secondly, with regard to data disaggregation and research implications, future research should consider academic unit-level data at UNH and the UofA, as well as for a study on any other university that employs RCM. Similar to the previous research implication, an analysis of data disaggregated at the academic unit level could provide university leaders and deans with greater insight on which colleges and schools were most compliant with controlling costs. For example, among the 13 colleges and schools at UNH, an analysis of RCM's impact on costs using academic-level cost data could elucidate which units increased or decreased costs. This would entail an expansion of the IPEDS finance surveys for all postsecondary institutions. Again, this implication would

provide university leaders with additional evidence to make specific policy recommendations for whichever units increased costs the most.

Lastly, regarding research implications, the use of disaggregated academic unit-level data in conjunction with qualitative techniques, such as interviews, would have provided further insight into where (in which colleges and schools) and why RCM caused total operating costs to increase at UNH and UofA. Specifically, because RCM is both a management tool and budgeting system, it is difficult to discern or speculate regarding why the treatment effects ranged widely without further research (e.g., such as interviews). Was it due to the administrative requirements for operating RCM, as suggested by Jaquette and associates (2008)? Was it due to behavioral changes among university administrators? Or, was it a combination of both administrative requirements and behavioral changes? More research is necessary to uncover which components within total operating costs (e.g., expenses on instruction, administration, and student services) were most affected by RCM.

### **Recommendations for Future Research**

Because scholars have not yet developed a comprehensive body of empirical research on RCM, recommendations for future research abound. Previous literature on RCM has only two revealed two broad findings. Specifically, prior research (Deering & Sá, 2014; Jaquette et al., 2018) has shown that universities primarily implemented RCM to enhance their financial positions (i.e., to generate additional revenue and minimize costs). Moreover, previous studies (Deering & Sá, 2018; Gros Louis & Thompson, 2002; Hearn et al., 2006; Lang, 2002) show that institutions have realized mixed experiences



(i.e., positive and negative) with RCM. Additionally, due to the dearth of RCM scholarship, other findings regarding RCM have been institution-specific and unconnected to any systematic investigation of its impact. These findings include perceptions of RCM budgeting as a structural process (Cekic, 2010); RCM's impact on faculty workload (McBride et al., 2000); and RCM's impact on graduation rates (Rutherford & Rabovsky, 2017). This study contributes to the limited literature on RCM, revealing RCM's impact on costs at two public research universities in the United States. However, the body of scholarship on RCM requires further development with regard to topics for exploration and methodological approaches.

As it relates to topics for exploration, future research should consider at least three general areas. First, scholars should examine RCM's impact on critical university outcomes, such as enrollment, profitability, administrative costs, the number of academic programs, donative revenue, and rankings. Within each of these outcomes, scholars should investigate how RCM's effect may impact various campus communities (e.g., faculty, staff, students, and administrators) and programs. Previous research has not considered any of these outcomes explicitly. Given the substantial time and monetary investment it takes to implement RCM – as noted in this study with respect to UNH and the UofA and confirmed by scholars and practitioners (Curry et al., 2013; Jaquette et al., 2018; Strauss & Curry, 2002; Whalen, 1991) – an examination of RCM's impact on each of these topics could provide university administrators and policymakers with the evidence necessary to discern if the implementation of RCM is worthwhile.

Second, with regard to future research topics, scholars should investigate and document the variability in RCM models across universities that employ RCM. For

example, researchers could consider differences in RCM models based on the length of time institutions have operated RCM (i.e., new versus old). Scholars could explore to what extent universities' outcomes might be different based on the number of years operating RCM. Additionally, with regard to RCM model variability, scholars should examine differences in RCM models based on funding methodology. For example, a consulting report by Attis et al. (2016) described several ways in which some public research universities allocate funding. Iowa State University allocates undergraduate revenue to responsibility centers in a 75/25 fashion (i.e., 75% of revenue is allocated based on student credit hours and the remaining 25% is allocated based on program enrollment). The University of Michigan does so in a 50/50 fashion and the University of Minnesota does so in a 25/75 fashion. As noted in *Chapter 1: Introduction*, each of these funding methods provides different incentives for increasing program enrollment and course enrollment. However, what remains unknown is whether those incentives make a difference, and if so, to what extent. Finally, with regard to RCM model variability, researchers should consider differences in how universities operate RCM. For example, Deering and Lang (2017) suggest that some universities fail to fully implement RCM and instead use a hybrid approach. A hybrid model combines RCM with a centralized or other approach. Scholars should investigate differences in university outcomes, if any, based on the use of a pure RCM model (i.e., those that are fully implemented) compared to a hybrid model.

With regard to methodological approaches, future research on RCM should employ quantitative techniques that yield generalizable results and techniques that combine qualitative and quantitative research designs. As it relates to the former, the lack

of generalizable knowledge regarding RCM is due to the inability of researchers to employ appropriate research methods to account for: a) the relatively small number of universities that use RCM; b) the variability in RCM models across universities; and c) the time differences in which universities adopted RCM. As a consequence, scholars have mostly investigated RCM in a case-by-case manner, with exception of Rutherford and Rabovsky (2017). This study is no different from previous research in that regard – specifically, this study examined RCM in a case-by-case manner for two research universities. The use of a quasi-experimental approach that could yield generalizable results, such as the generalized synthetic control method. The generalized synthetic control method can take into account multiple treated units (e.g., multiple universities that adopted RCM) and produce broader causal results regarding the effects of a treatment, policy, or intervention (Xu, 2017). Future research on RCM should incorporate the generalized synthetic control method to provide more conclusive evidence regarding its utility. This, in turn, could provide university administrators and policymakers with a better understanding of RCM’s impact and effectiveness.

Finally, future research should use mixed methods research designs for studies on RCM. For example, in the context of this study, if qualitative interviews were used, they could have provided additional context around the principal-agent relationship between central administration and deans. Specifically, interviews with central administrators and deans might allow future researchers to understand the shirking behavior that may have occurred at UNH and UofA with respect to the increases in total operating costs. Additionally, with respect to Bowen’s RTC, interviews might reveal how additional revenue could influence costs. For example, it could be the case that RCM caused costs

to decrease in some areas, however, instead of saving the cost-savings, deans instead repurposed them to spend on other things, such as activities that increase the prestige and influence of the institution. Qualitative research is needed to substantiate this speculation. Ultimately, the use of SCM and interviews could elucidate a fuller picture of RCM and help university leaders develop specific recommendations for policy and practice.

## Appendix A

Table A1. Public Universities in the US that have Implemented RCM

<b>Institution Name</b>	<b>RCM Implementation Year</b>
Indiana University - Bloomington	1988-89
Indiana University of Pennsylvania - Main Campus	1988-89
University of Pittsburgh - Pittsburgh Campus	1991-92
University of Minnesota - Twin Cities	1995-96
UCLA	1996-97
Temple University	1996-97
University of Michigan - Ann Arbor	1997-98
University of Illinois - Urbana Champaign	1999-00
University of New Hampshire - Main Campus	1999-00
Ohio State University - Main Campus	2002-03
Central Michigan University	2007-08
University of Cincinnati - Main Campus	2008-09
Iowa State University	2008-09
University of Missouri Kansas City	2009-10
Kent State University at Kent	2009-10
University of Florida	2009-10
University of Delaware	2009-10
Texas Tech University	2011-12
University of Oregon	2011-12
University of Washington - Seattle	2011-12
University of California Davis	2012-13
University of New Mexico - Main Campus	2013-14
University of South Dakota	2013-14
University of Vermont	2014-15
University of Virginia - Main Campus	2014-15
Ohio University	2014-15
University of Arizona	2015-16
University of North Dakota	2015-16
Rutgers University	2015-16
East Tennessee State University	2016-17
Tennessee Tech University	2016-17
University of Louisville	2017-18
Northern Kentucky University	2017-18
Virginia Commonwealth University	2017-18

<b>Institution Name</b>	<b>RCM Implementation Year</b>
University of North Carolina Chapel Hill	2017-18
University of Alabama Birmingham	2018-19
University of South Carolina	2018-19
Western Kentucky University	2018-19

Table A2. Overview of RCM Operations at Institutions in the Study

	<b>University of New Hampshire - Main Campus</b>	<b>University of Arizona</b>
<b>First Year of RCM Implementation</b>	July 2000	July 2015
Responsibility Centers	Colleges (academic units); Research; and Auxiliaries	Colleges (academic units); Auxiliaries
Central Administration & Support Centers	Academic Affairs, Library, IT, General Administration, Advancement, Enrollment Management Institutional Accounts, Facilities, Research	Administration, Business Services, Student Support, Research Support, Public Service, Facilities
Undergraduate Tuition and Fee Revenue	2% to Library; 15% to Division of Continuing Education; 83% to academic unit based on weighted credit hours taught (averaged over 2 years and weighted based on expense per credit hour)	Pooled; 75% student credit hour and 25% student's major
Graduate Tuition and Fee Revenue	2% to Library; 98% to an academic unit	Student by student; 75% student credit hour and 25% student's major
State Appropriations	Program Allocation Units are funded first then the remaining is allocated as follows: 20% to Library; 30% to academic and research units based on faculty salaries (excluding grad students and extension faculty); the remaining funds are placed into a "hold harmless/strategic fund"	Is the primary source of the subvention pool. Allocated to academic units, that when combined with other allocated funds, will provide colleges with a budget sufficient to cover their historical budget and the costs of support and facilities

	<b>University of New Hampshire - Main Campus</b>	<b>University of Arizona</b>
Research Revenue	13% to Principal Investigator; 66.5% to the research unit; 18.5% to VP of Research; 2% to Library	100% Indirect credit recovery is returned to the college
Funding Source of Subvention Pool	State Appropriations, Interest Income	State Appropriations
Cost Allocation of Support Center Services	Facilities Services is based on space allocations per square footage. Other overhead expenses are funded through two assessments: academic affairs and general.	30.96% tax of undergraduate tuition; 12.38% tax of graduate tuition; 2.75% tax of both tuitions for Strategic Initiative Fund; Annual facilities assessment fee based on square footage
Faculty/Staff Salaries	Funded by the academic units/responsibility centers	Funded by the academic units/responsibility centers and subvention funds
Fringe Benefits	Funded by the academic units/responsibility centers	Funded by the academic units/responsibility centers and subvention funds
Travel, Equipment, Supplies, Other	Funded by the academic units/responsibility centers	Funded by the academic units/responsibility centers and subvention funds
Institutional Overhead	Academic Affairs Assessment "tax" is paid by academic units. General Assessment "tax" is paid by all units. (assessments are based on 50% of personnel expenses and 50% of all revenues)	Allocated from the subvention fund and from revenue-generating auxiliaries
Notes	The RCM allocation rules above are based on the first RCM model at UNH – fiscal years 2001-2006. (UNH RCM Operating Manual, 2017)	

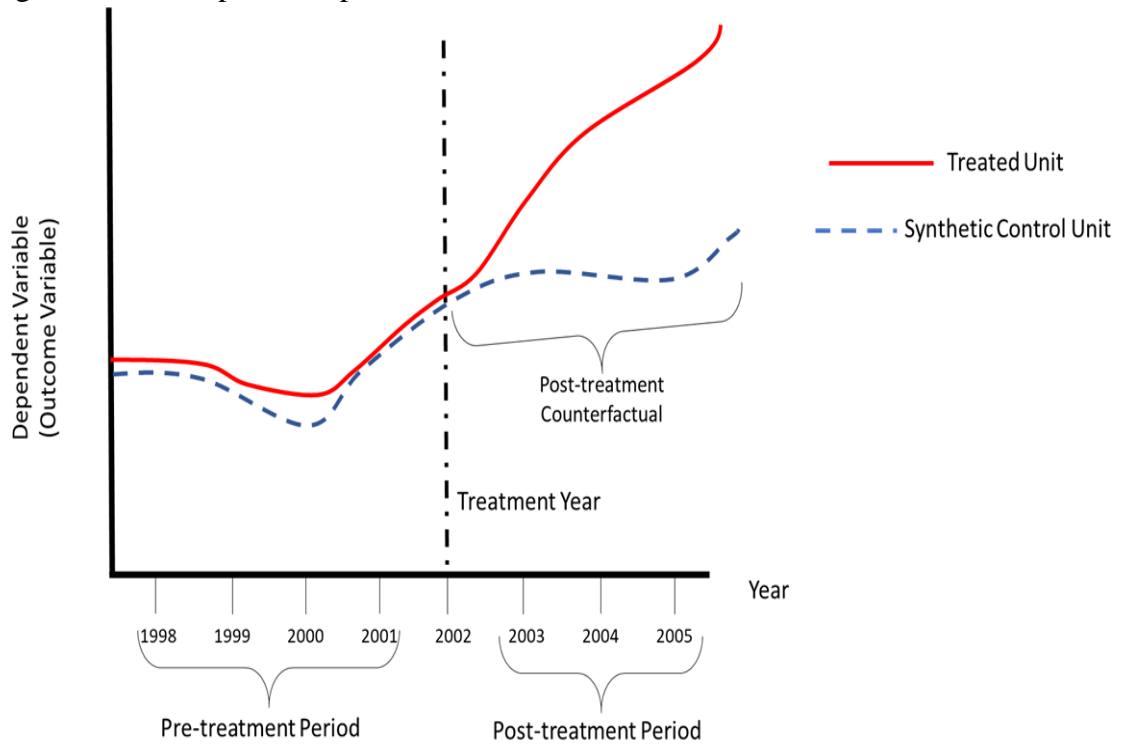
Table A3. Data and Variables in the Study

<b>Variable Name</b>	<b>Description</b>	<b>Sample Range</b>	<b>Source</b>
Total Operating Costs (outcome variable)	The sum of expenditures on administration, instruction, and student services.	<ul style="list-style-type: none"> <li>● UNH (1989-90) to 2004-05)</li> <li>● <b>University of Arizona</b> (1989-90 to 2017-18)</li> </ul>	IPEDS
Full-time Equivalent Undergraduate Enrollment	The number of full-time undergraduate students plus one-third of part-time undergraduate students enrolled.	<ul style="list-style-type: none"> <li>● UNH (1989-90) to 2004-05)</li> <li>● <b>University of Arizona</b> (1989-90 to 2017-18)</li> </ul>	IPEDS
Graduate Enrollment (headcount)	The number of graduate students enrolled.	<ul style="list-style-type: none"> <li>● UNH (1989-90) to 2004-05)</li> <li>● <b>University of Arizona</b> (1989-90 to 2017-18)</li> </ul>	IPEDS
Full-time Faculty	The number of full-time faculty.	<ul style="list-style-type: none"> <li>● UNH (1989-90) to 2004-05)</li> <li>● <b>University of Arizona</b> (1989-90 to 2017-18)</li> </ul>	IPEDS
Research Expenditures	The total dollars spent on research.	<ul style="list-style-type: none"> <li>● UNH (1989-90) to 2004-05)</li> <li>● <b>University of Arizona</b> (1989-90 to 2017-18)</li> </ul>	IPEDS
Average Faculty Salary	The average faculty salary.	<ul style="list-style-type: none"> <li>● UNH (1989-90) to 2004-05)</li> <li>● <b>University of Arizona</b> (1989-90 to 2017-18)</li> </ul>	IPEDS
STEM Degrees Conferred (a proxy for academic program mix)	The proportion of students graduating with degrees in science, technology, engineering, and mathematics out of the total number of bachelor's degrees conferred.	<ul style="list-style-type: none"> <li>● UNH (1989-90) to 2004-05)</li> <li>● <b>University of Arizona</b> (1989-90 to 2017-18)</li> </ul>	IPEDS



<b>Variable Name</b>	<b>Description</b>	<b>Sample Range</b>	<b>Source</b>
Tuition and Fee Revenue	Total dollars generated from tuition and fees.	<ul style="list-style-type: none"> <li>● UNH (1989-90) to 2004-05)</li> <li>● <b>University of Arizona</b> (1989-90 to 2017-18)</li> </ul>	IPEDS
State Appropriation Revenue	Total dollars received from state appropriations.	<ul style="list-style-type: none"> <li>● UNH (1989-90) to 2004-05)</li> <li>● <b>University of Arizona</b> (1989-90 to 2017-18)</li> </ul>	IPEDS
Revenues from Private Gifts, Grants, and Contracts	Total dollars received from private gifts, grants, and contracts.	<ul style="list-style-type: none"> <li>● UNH (1989-90) to 2004-05)</li> <li>● <b>University of Arizona</b> (1989-90 to 2017-18)</li> </ul>	IPEDS
Percent of Tuition and Fee Revenue out of Total Revenue	The percent of tuition and fee revenue out of total revenue.	<ul style="list-style-type: none"> <li>● UNH (1989-90) to 2004-05)</li> <li>● <b>University of Arizona</b> (1989-90 to 2017-18)</li> </ul>	IPEDS
Percent of State Appropriation Revenue out of Total Revenue	The percent of state appropriation revenue out of total revenue.	<ul style="list-style-type: none"> <li>● UNH (1989-90) to 2004-05)</li> <li>● <b>University of Arizona</b> (1989-90 to 2017-18)</li> </ul>	IPEDS

Figure A1. A Simple Example of SCM



## Appendix B

**Sensitivity Analysis (Leave-one-out Test Results)****University of New Hampshire**

Table B1. Synthetic Control Unit for University of New Hampshire (Synthetic UNH with University of Vermont Removed)

<b>Synthetic Control Unit (synthetic UNH)</b>			
<b>UnitID</b>	<b>Institutions (synthetic controls)</b>	<b>State</b>	<b>Weight (w)</b>
231624	College of William and Mary	VA	0.456
176080	Mississippi State University	MS	0.438
169248	Central Michigan University	MI	0.105
180461	Montana State University	MT	0
200332	North Dakota State University-Main Campus	ND	0
166513	University of Massachusetts-Lowell	MA	0

Table B2. Pre-treatment Estimates for University of New Hampshire (Synthetic UNH with University of Vermont Removed)

<b>Predictor Variable</b>	<b>University of New Hampshire (Treated Unit)</b>	<b>Synthetic University of New Hampshire (Control Unit)</b>	<b>Synthetic University of New Hampshire (without University of Vermont)</b>
Total Operating Cost (USD in millions) (1991)	\$82.06	\$82.87	\$68.91
Total Operating Cost (USD in millions) (1999)	\$116.69	\$118.26	\$110.04
Full-time Equivalent (FTE) Undergraduate Enrollment (1991)	10,197	8,838	8,753
Full-time Equivalent (FTE) Undergraduate Enrollment (1999)	10,772	8,930	9,183
Graduate Enrollment (headcount) (1991)	2,116	1,395	2,154
Graduate Enrollment (headcount) (1999)	2,718	2,087	2,756

<b>Predictor Variable</b>	<b>University of New Hampshire (Treated Unit)</b>	<b>Synthetic University of New Hampshire (Control Unit)</b>	<b>Synthetic University of New Hampshire (without University of Vermont)</b>
Percent (%) of STEM bachelor's degrees produced out of total conferred(1991)	25.0	26.9	25.2
Percent (%) of STEM bachelor's degrees produced out of total conferred (1999)	27.8	28.0	29.0
Full-time Faculty (1991)	558	538	607
Full-time Faculty (1999)	609	514	667
Average Faculty Salary (9-month equated salary) (1991)	\$44,849	\$42,602	\$44,892
Average Faculty Salary (9-month equated salary) (1999)	\$56,725	\$53,453	\$56,677
Percent (%) of State Appropriation Revenue out of Total Revenue (1991)	19.0	26.2	34.3
Percent (%) of State Appropriation Revenue out of Total Revenue (1999)	16.0	19.0	29.6
Percent (%) of Tuition and Fee Revenue out of Total Revenue (1991)	33.3	28.6	20.8
Percent (%) of Tuition and Fee Revenue out of Total Revenue (1999)	34.3	32.2	24.5
Research Expenditures (USD in millions) (1991)	\$32.85	\$25.08	\$31.69
Research Expenditures (USD in millions) (1999)	\$53.36	\$38.55	\$46.67
Revenue from Private Gifts, Grants, and Contracts (USD in millions) (1991)	\$11.67	\$12.74	\$7.92

Predictor Variable	University of New Hampshire (Treated Unit)	Synthetic University of New Hampshire (Control Unit)	Synthetic University of New Hampshire (without University of Vermont)
Revenue from Private Gifts, Grants, and Contracts (USD in millions) (1999)	\$18.72	\$19.42	\$15.81
State Appropriation Revenue (USD in millions) (1991)	\$36.99	\$38.32	\$59.74
State Appropriation Revenue (USD in millions) (1999)	\$48.81	\$44.47	\$84.17
Tuition and Fee Revenue (USD in millions) (1991)	\$64.60	\$53.67	\$31.31
Tuition and Fee Revenue (USD in millions) (1999)	\$104.84	\$87.17	\$58.14

Figure B1. Graph of Treatment Effects of RCM’s Impact on Operating Cost at University of New Hampshire (Leave-one-out Test)

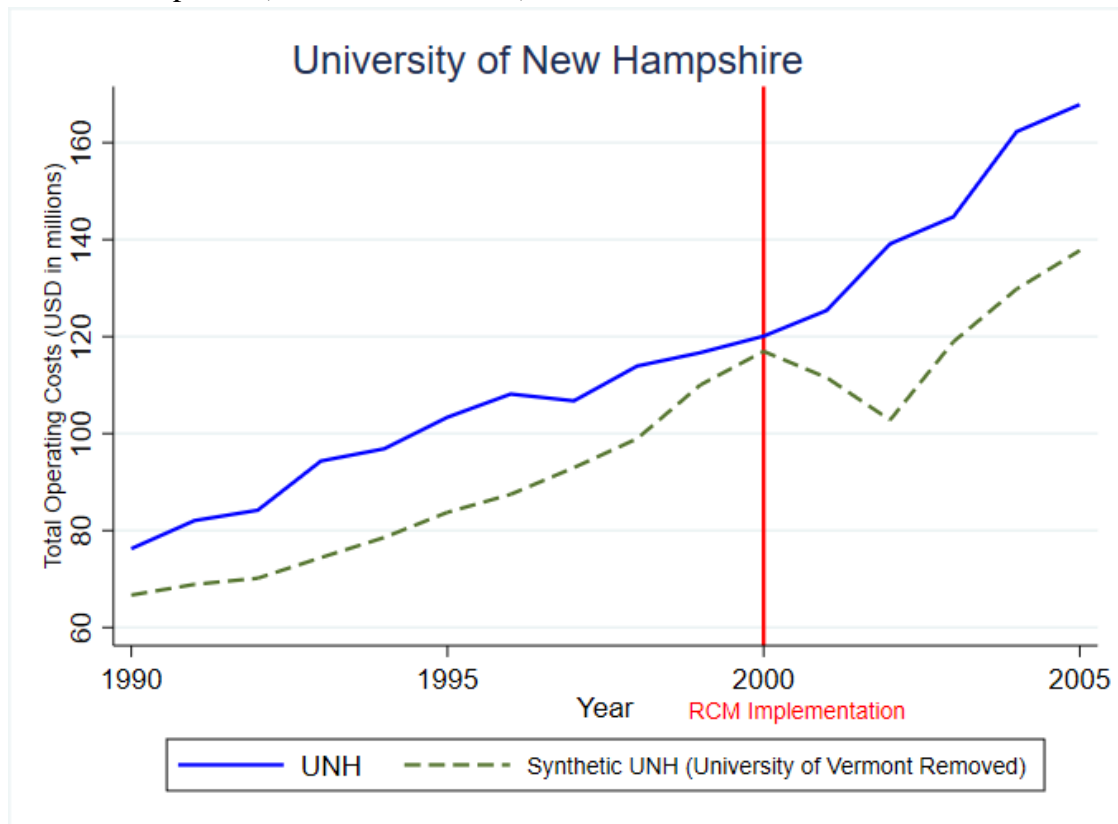


Table B3. Treatment Effects of RCM’s Impact on Operating Cost at University of New Hampshire (Leave-one-out Test)

<b>Total Operating Costs (USD in millions)</b>					
<b>Post-Treatment Period</b>	<b>Year</b>	<b>UNH</b>	<b>Synthetic UNH (University of Vermont Removed)</b>	<b>Treatment Effect</b>	<b>P-Value</b>
1	2001	\$125.41	\$111.52	\$13.89	0.500
2	2002	\$139.13	\$102.80	\$36.34	0.167
3	2003	\$144.69	\$118.93	\$25.76	0.333
4	2004	\$162.25	\$129.79	\$32.47	0.333
5	2005	\$167.86	\$137.76	\$30.10	0.333

**University of Arizona**

Table B4. Synthetic Control Unit for University of Arizona (Synthetic UofA with University of Georgia Removed)

<b>Synthetic Control Unit (synthetic UofA)</b>			
<b>UnitID</b>	<b>Institutions (synthetic controls)</b>	<b>State</b>	<b>Weight (w)</b>
171100	Michigan State University	MI	0.35
133951	Florida International University	FL	0.219
240444	University of Wisconsin-Madison	WI	0.18
218663	University of South Carolina-Columbia	SC	0.171
110680	University of California-San Diego	CA	0.056
110635	University of California-Berkeley	CA	0.024
233921	Virginia Polytechnic Institute and State University	VA	0
228778	The University of Texas at Austin	TX	0
228723	Texas A & M University-College Station	TX	0

Table B5. Pre-treatment Estimates for University of Arizona (Synthetic UofA with University of Georgia Removed)

<b>Predictor Variable</b>	<b>University of Arizona (Treated Unit)</b>	<b>Synthetic University of Arizona (Control Unit)</b>	<b>Synthetic University of Arizona (without University of Georgia)</b>
Total Operating Cost (USD in millions) (2000)	\$400.73	\$404.65	\$393.27
Total Operating Cost (USD in millions) (2009)	\$576.43	\$604.75	\$629.08
Total Operating Cost (USD in millions) (2014)	\$881.36	\$865.98	\$849.40
Full-time Equivalent (FTE) Undergraduate Enrollment (2000)	23,155	21,558	23,342
Full-time Equivalent (FTE) Undergraduate Enrollment (2009)	27,215	25,033	27,293
Full-time Equivalent (FTE) Undergraduate Enrollment (2014)	29,491	27,190	30,346
Graduate Enrollment (headcount) (2000)	6,944	6,387	6,981
Graduate Enrollment (headcount) (2009)	8,341	7,643	7,997
Graduate Enrollment (headcount) (2014)	8,951	8,984	9,880
Percent (%) of STEM bachelor's degrees produced out of total conferred (2000)	26.4	28.3	27.2
Percent (%) of STEM bachelor's degrees produced out of total conferred (2009)	28.9	27.9	25.7
Percent (%) of STEM bachelor's degrees produced out of total conferred (2014)	31.2	33.2	32.0
Full-time Faculty (2000)	1,348	1,384	1,344
Full-time Faculty (2009)	1,593	1,538	1,600

<b>Predictor Variable</b>	<b>University of Arizona (Treated Unit)</b>	<b>Synthetic University of Arizona (Control Unit)</b>	<b>Synthetic University of Arizona (without University of Georgia)</b>
Full-time Faculty (2014)	1,561	1,676	1,720
Average Faculty Salary (9-month equated salary) (2000)	\$67,451	\$70,858	\$66,114
Average Faculty Salary (9-month equated salary) (2009)	\$87,187	\$92,385	\$87,581
Average Faculty Salary (9-month equated salary) (2014)	\$92,880	\$99,577	\$94,361
Percent (%) of State Appropriation Revenue out of Total Revenue (2000)	34.2	36.3	34.2
Percent (%) of State Appropriation Revenue out of Total Revenue (2009)	25.5	25.2	23.3
Percent (%) of State Appropriation Revenue out of Total Revenue (2014)	15.7	17.7	14.6
Percent (%) of Tuition and Fee Revenue out of Total Revenue (2000)	17.1	17.4	20.0
Percent (%) of Tuition and Fee Revenue out of Total Revenue (2009)	25.9	27.2	31.5
Percent (%) of Tuition and Fee Revenue out of Total Revenue (2014)	36.6	34.6	36.3
Research Expenditures (USD in millions) (2000)	\$235.74	\$231.00	\$206.46
Research Expenditures (USD in millions) (2009)	\$385.47	\$344.42	\$322.75
Research Expenditures (USD in millions) (2014)	\$451.27	\$460.12	\$419.22



<b>Predictor Variable</b>	<b>University of Arizona (Treated Unit)</b>	<b>Synthetic University of Arizona (Control Unit)</b>	<b>Synthetic University of Arizona (without University of Georgia)</b>
Revenue from Private Gifts, Grants, and Contracts (USD in millions) (2000)	\$75.61	\$82.07	\$84.74
Revenue from Private Gifts, Grants, and Contracts (USD in millions) (2009)	\$78.16	\$73.69	\$77.33
Revenue from Private Gifts, Grants, and Contracts (USD in millions) (2014)	\$78.29	\$95.69	\$81.93
State Appropriation Revenue (USD in millions) (2000)	\$320.91	\$328.77	\$287.84
State Appropriation Revenue (USD in millions) (2009)	\$371.49	\$344.61	\$302.14
State Appropriation Revenue (USD in millions) (2014)	\$287.49	\$303.55	\$255.36
Tuition and Fee Revenue (USD in millions) (2000)	\$160.65	\$162.14	\$180.25
Tuition and Fee Revenue (USD in millions) (2009)	\$377.35	\$369.23	\$401.59
Tuition and Fee Revenue (USD in millions) (2014)	\$670.32	\$599.11	\$625.36

Figure B2. Graph of Treatment Effects of RCM’s Impact on Operating Cost at University of Arizona (Leave-one-out Test)

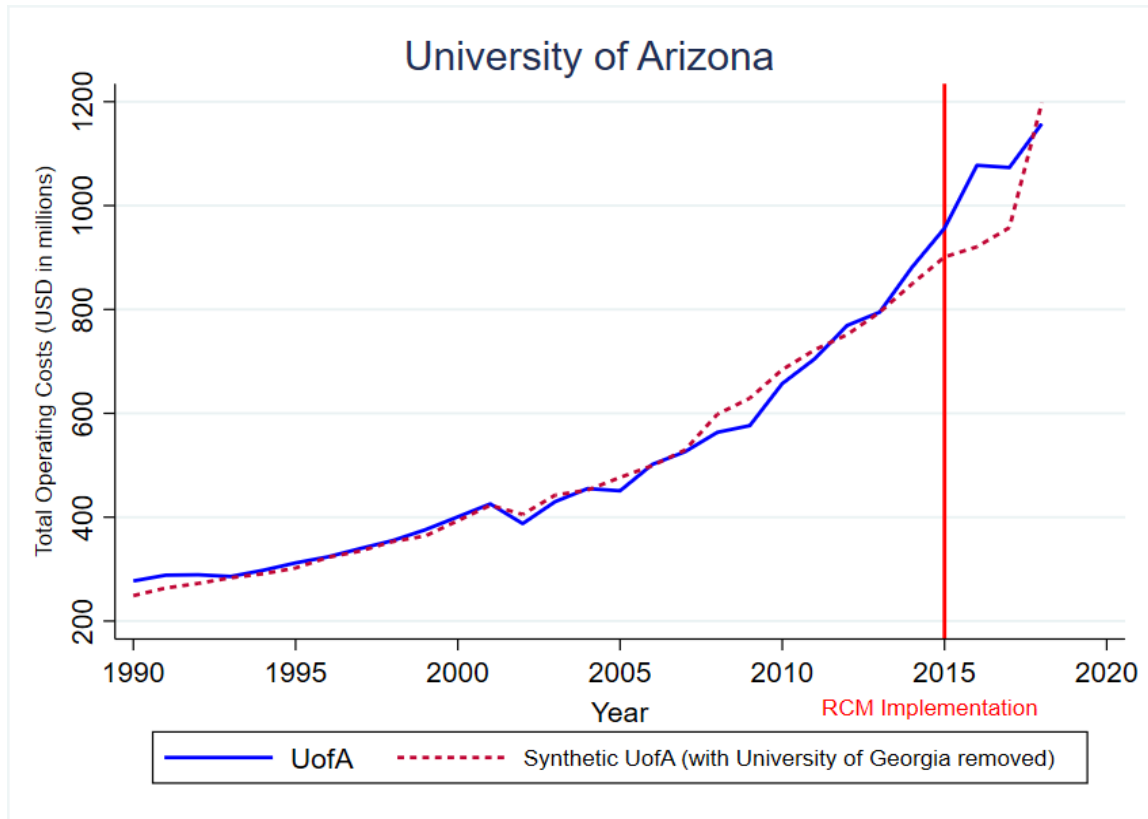


Table B6. Treatment Effects of RCM’s Impact on Operating Cost at University of Arizona (Leave-one-out Test)

Total Operating Costs (USD in millions)					
Post-Treatment Period	Year	UofA	Synthetic UofA (without University of Georgia)	Treatment Effect (UofA - Synthetic UofA)	P-Value
1	2016	\$1,077.51	\$920.62	\$156.89	0.556
2	2017	\$1,073.27	\$957.52	\$115.76	0.778
3	2018	\$1,157.84	\$1,198.10	-\$40.26	1

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