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Financial Incentives for California Community Colleges: Impacts on District Revenue, Student Financial Aid Receipt, and Degree Production

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Financial Incentives for California Community Colleges: Impacts on District Revenue, Student Financial Aid Receipt, and Degree Production

By

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Abstract

The California Community College (CCC) system serves an integral role in the state's public education. Serving more than 2.1 million students annually across 116 colleges, it is the largest higher education system in the nation. It provides students with remedial education, precollegiate instruction, and workforce preparation. Moreover, a substantial share of graduates from California's four-year universities begin their coursework in the CCC system.

The state uses a centralized funding formula to apportion CCC revenue. This formula is crucial in allocating resources across districts, colleges, and students in a manner that reflects the state's priorities for the system's many educational functions and student populations. Historically, the state used an enrollment-based funding formula that weighted funding for all students equally. However, in 2018, the state adopted the Student-Centered Funding Formula (SCFF) which represented a substantial shift in the state's funding priorities for the CCC system.

The SCFF funds districts according to enrollment levels, equity, and student success. The equity component is based on a district's counts of financial aid recipients. The student success component is based on a district's counts of students who achieve various academic benchmarks including certificate or associate degree completion. This component is also weighted according to the number of financial aid recipients who achieve a given benchmark.

The SCFF poses significant implications for the CCC system. The added equity and student success components comprise roughly a third of total apportionment funding. Administrators thus face increased financial incentives to effectively administer financial aid to students and to improve student performance along the state-set metrics. If districts and colleges successfully respond to the SCFF's financial

incentives, the policy may improve student outcomes through reformed financial aid administration and/or increased completion of certificates and degrees. However, the failure to respond to these financial incentives may result in revenue shortfalls that limit the operational effectiveness of districts and colleges.

This dissertation is comprised of three papers in which I explore the SCFF's effects on district revenue, student financial aid receipt, and degree production in the CCC system. In the first paper, I provide a detailed discussion of CCC apportionment. I describe the funding mechanics of the SCFF and the enrollment-based funding formula that preceded it. I also use ordinary least squares modeling to estimate the impact of the SCFF on district revenue in its first operational year. For this analysis, I use CCC apportionment data in 2017 and 2018. I find that districts serving higher proportions of lower-income students experienced an increase in revenue from the SCFF relative to the prior formula, on average. In turn, the SCFF increased progressivity in CCC funding.

In the second paper, I measure the SCFF's effects on student receipt of Pell Grants and Promise Grants. I draw on student-level administrative data from the CCC system in the 2015-2019 period. I use an interrupted time series model to estimate effects on Pell and Promise Grant receipt systemwide. I also use comparative interrupted time series models to estimate differential effects across college groups. I find a systemwide increase in Pell Grant receipt—but not Promise Grant receipt—associated with SCFF. These effects did not show substantial differences across college groups that were financially affected or unaffected by the SCFF's financial incentives. However, heterogeneity in Pell receipt was driven by the extent to which a college could expand awarding among students who likely would have been eligible non-recipients in the absence of the SCFF.

In the third paper, I measure the SCFF's effects on certificate and degree production. I draw on student-level administrative data from the CCC system in the 2015-2018 period. I use an interrupted time series model to estimate systemwide changes in certificate and degree awarding after the adoption of the SCFF. I also use comparative interrupted time series models to estimate differential college effects. I find an increase in certificate and traditional associate degree awarding associated with the SCFF. These gains are impressive considering that this analysis uses only a single year of post-SCFF data. However, Associate Degrees for Transfer exhibit null effects associated with the SCFF. I find modest evidence that heterogeneity in effects across colleges was driven by the extent to which a college was affected by the SCFF's financial incentives. Across two distinct grouping methods, college groups that were more affected exhibited somewhat larger awarding gains in most degree types than college groups that were less affected. However, partially due to power limitations, the differences between more- and less-affected colleges were generally not significant, so these results are suggestive but not conclusive.

This dissertation makes several contributions to existing literature. The first paper reviews CCC funding in a level of detail that, to my knowledge, has not been covered in nearly two decades. The second paper is novel in its topic since the SCFF is unique in its use of financial aid receipt as a student metric. These results offer encouraging evidence that financial aid incentives may be efficacious in increasing student financial aid receipt. Finally, the third paper contributes to a relatively larger body of literature on the effects of performance funding policies on student certificate and degree completion. While prior research largely finds that performance funding policies do not benefit student academic attainment, my results find early evidence of gains in certificate and associate degree completion associated with the SCFF.

Acknowledgements and Dedication

First, I thank my adviser, Cassie Hart. Cassie—From the moment I arrived at Davis, you have been an incredible teacher, mentor, and, at times, life coach. You have shown me the patience and attention to detail that is required to do excellent research. You were the reason I moved across the country to study at Davis and, largely, the reason I finished my doctorate. For all of this and more, I am incredibly grateful.

Next, I thank Michal Kurlaender and Paco Martorell for serving on my dissertation committee. I am very fortunate that you both pointed me towards the topic of community college funding and the research questions that comprise this dissertation. You also gave me opportunities to assist in your research projects which prepared me to conduct my own studies.

I also thank other paper reviewers for their feedback. Heather Rose—Your prior work in formula funding helped shape the analysis in my first paper. Betsey Friedmann—You provided consistent feedback throughout my writing process and mentorship in working with the administrative datasets I use in this dissertation. Susanna Cooper and Christian Osmena—Your depth of knowledge surrounding California's education governance and policy was greatly beneficial to my writing on community college funding.

Last but not least, I thank the incomparable Mary Reid from the School of Education for helping me navigate the administrative processes involved in completing my doctorate which, in my case, was no small feat.

I dedicate this dissertation to Daniel Dumile, who tragically passed last year. Your writing is an inspiration to my own and your music was present throughout my completion of this work.

Table of Contents

Abstract ii

Acknowledgements and Dedication v

Table of Contents vi

List of Tables and Figures ix

Paper 1: District Apportionment in the California Community College System 1

Abstract 2

Introduction 3

CCC Background 4

CCC Revenue Sources 8
- District Budgeting and the General Fund 9
- District General Fund Revenue Sources 10
- State Budgeting under Proposition 98 13

Allocating State Revenues across Community College Districts 16

Historical Approaches to California Funding Formulas 20
- Enrollment-Based Funding Formula 21
  - Basic Allocation 22
  - Instructional Revenue 23
  - Base Revenue 24
  - Inflation Funding 25
  - Additional EBFF Mechanisms 25
- Student-Centered Funding Formula 26
  - Basic Allocation 27
  - Instructional Revenue 27
  - Supplemental Allocation 28
  - Student Success Allocation 29
  - Base Revenue 32
  - Inflation Funding 32
  - Hold Harmless 33

Evaluating Funding Changes under the SCFF 33
- Sample 34
- Measures and Data 34
  - District Apportionment 34
  - District Indicators 35
- Descriptive Statistics 37
- Matrix of Correlations 38
- Variability in SCFF Apportionment Effects 39
- Relationship between District Funding and Student Income across Formulas 45

Conclusion 47

Glossary ... 50
References ... 52
Appendix A: District Budgeting ... 60
Appendix B: The Program-Based Funding Formula ... 63
Appendix C: Growth, Stability, and Restoration Funding ... 64
Growth Funding ... 64
Stability and Restoration ... 65
SCFF Changes ... 67
Appendix D: Regression Results ... 68

Paper 2: Impact of Financial Aid Incentives on Student Receipt in the California Community College System ... 72

Abstract ... 73
Introduction ... 74
Background ... 76
Prior Literature ... 76
California Community Colleges and the Student-Centered Funding Formula ... 78
Pell Grants ... 81
Promise Grants ... 82
Research Questions ... 84
Data and Methods ... 84
Data Construction ... 84
Analytical Samples ... 86
Pell Sample ... 86
Promise Sample ... 88
Summary Statistics ... 89
Methods ... 91
Interrupted Time Series ... 92
Comparative Interrupted Time Series ... 94
Event-Study with Comparison Groups ... 96
Grouping by Community Supported (CS) Status ... 97
Summary Statistics for Pell and Promise Samples by College CS Status ... 100
Grouping by Baseline Take-Up Rate ... 102
Summary Statistics for Take-Up-Based Groups in the Pell Sample ... 104
Main Estimation Results ... 106
ITS Estimates of Systemwide Effects ... 106
Estimates of Heterogeneous Effects by CS Status ... 107
Estimates of Heterogeneous Effects by Baseline Pell Take-Up ... 111
Discussion ... 115
Conclusion ... 118
References ... 120

Appendix A: Satisfactory Academic Progress ... 124
Introduction to Satisfactory Academic Progress ... 124
Coding SAP Requirements for Pell Eligibility ... 124
Coding SAP Requirements for Promise Eligibility ... 126

Appendix B: Common Trends by CS Status and Baseline Pell Take-Up ... 127

Appendix C: Alternate CS Grouping Method ... 130

Appendix D: CITS Coefficients Used to Estimate Total Effects by Spring 2020 ... 134

Paper 3: Impact of Degree Incentives on Degree Production in the California Community College System ... 136

Abstract ... 137

Introduction ... 138

Background ... 139
Performance Funding in Higher Education ... 139
Theoretical Framework ... 141
Prior Literature ... 142
Qualitative Results of PF Adoption ... 142
Quantitative Results of PF Adoption among Universities ... 143
Quantitative Results of PF Adoption among Community Colleges ... 144
California Community Colleges and the Student-Centered Funding Formula ... 147
Certificates, Associate Degrees, and ADTs ... 152

Research Questions ... 153

Data and Methods ... 153
Data Construction ... 153
Analytical Samples ... 154
Degree Counts ... 155
College-Level Student Covariates ... 155
Summary Statistics ... 156

Methods ... 158
Interrupted Time Series ... 159
Comparative Interrupted Time Series ... 160
Grouping by Community Supported (CS) Status ... 162
Summary Statistics by College CS Status ... 163
College Awarding Trends by CS Status ... 165
Grouping by Baseline Pell Receipt Rate ... 166
Summary Statistics for High and Low-Pell College Groups ... 168
College Awarding Trends across High- and Low-Pell Colleges ... 171

Main Estimation Results ... 172
ITS Estimates of Systemwide Effects ... 173
Estimates of Heterogeneous Effects by CS Status ... 174
Estimates of Heterogeneous Effects across High- and Low-Pell Colleges ... 177

Discussion ... 179

Conclusion ... 182

References 183
Appendix A: Regression Results with Logged Degree Counts 188

List of Tables and Figures

Paper 1: District Apportionment in the California Community College System
Figure 1.1. CCC Revenue per FTES 2010-2019 7
Figure 1.2. CCC FTES 2000-2020 8
Figure 1.3. CCC District General Fund Revenue Sources 11
Figure 1.4. CCC Proposition 98 Funds Sources and Allocations 14
Figure 1.5. CCC TCR by Revenue Source 17
Table 1.1. Total Computational Revenue and Apportioned Revenue in Practice 19
Table 1.2. Basic Allocation Schedule in 2006-07 23
Table 1.3. SCFF FTES Funding Schedule in 2018-19 28
Table 1.4. Student Success Allocation Schedule in 2018-19 31
Table 1.5. District Descriptive Statistics 38
Table 1.6. Matrix of Correlations 39
Figure 1.6. SCFF Apportionment Gains across CCC Districts 41
Table 1.7. OLS Results for SCFF Apportionment Changes 42
Figure 1.7. Relationship between TCR-per-FTES and Student Income in the EBFF and SCFF 46
Figure 1.A1. Aggregate CCC Revenue across District Funds 62
Table 1.D1. OLS Robustness Results for SCFF Apportionment Changes 68
Figure 1.D1. Relationship between TCR-per-FTES and Student Income in the EBFF and SCFF: Weighted Least Squares Results using FTES Weights 69
Table 1.D2. OLS Results for per-FTES Basic Allocation or Instructional Revenue in the EBFF 70
Table 1.D3. Change in Funding Progressivity Associated with the SCFF 71

Paper 2: Impact of Financial Aid Incentives on Student Receipt in the California Community College System
Table 2.1. Annual Counts of Student and College in the Pell and Promise Sample 88
Table 2.2. Summary Statistics for Pell and Promise Samples 90
Figure 2.1. Mean Model Outcomes in 2015-2019 94
Figure 2.2. Local Revenue Ratios across CS and non-CS Districts 98
Table 2.3. Summary Statistics for CS-Based Groups in the Pell and Promise Sample... 101
Figure 2.3. Distribution of Baseline Pell Take-up with Quartiles 103
Table 2.4. Summary Statistics for Take-Up Based Groups in the Pell Sample 105
Table 2.5. ITS Results for Systemwide Effects: Model Coefficients and Linear Combinations to Represent Effects by Spring 2020 107
Table 2.6. CITS Results with Financially-Affected and Financially-Unaffected College Groups: Linear Combinations to Represent Effects by Spring 2020 109
Figure 2.4. Event-Study Results with Financially Affected and Unaffected College Groups 111
Table 2.7. CITS Results with Take-Up Based Treatment and Control Groups: Linear Combinations to Reflect Effects by Spring 2020 113

Figure 2.5. Event-Study Results with Take-Up-Based Treatment and Control Groups 115
Figure 2.B1. Trends in Aid Outcomes Across CS and non-CS Colleges 128
Figure 2.B2. Trends in Aid Outcomes Across High and Low Take-Up Colleges.......... 129
Table 2.C1. Summary Statistics for CS-Based Groups in the Pell and Promise Sample 131
Table 2.C2. CITS Results with Financially Affected and Unaffected College Groups: Linear Combinations to Represent Effects by Spring 2020 132
Figure 2.C1. Event-Study Results with CS-Based Treatment and Control Groups 133
Table 2.D1. CITS Results with Financially Affected and Unaffected College Groups .. 134
Table 2.D2. CITS Results with Take-Up Based Treatment and Control Groups 135

Paper 3: Impact of Degree Incentives on Degree Production in the California Community College System

Table 3.1. Student Success Allocation Table 150
Table 3.2. Annual College Counts in the Certificate, Associate Degree, and ADT Samples 155
Table 3.3. Summary Statistics for All Colleges 157
Figure 3.1. Trends in Mean Awarding Outcomes 160
Table 3.4. Summary Statistics by College CS Status 164
Figure 3.2. Trends in Mean Awarding Outcomes by CS Status....................................... 166
Figure 3.3. Distribution of Baseline Pell Receipt Rate with Quartiles 168
Table 3.5. Summary Statistics for High- and Low-Pell College Groups 170
Figure 3.4. Trends in Mean Awarding Outcomes by CS Status....................................... 172
Table 3.6. ITS Results for Systemwide Effects 174
Table 3.7. CITS Results with Financially-Affected (non-CS) and Financially-Unaffected (CS) College Groups 175
Table 3.8. CITS Results with High- and Low-Pell Groups... 178
Table 3.A1. ITS Results for Systemwide Effects: Logged Results 189
Table 3.A2. CITS Results with Financially-Affected and Financially-Unaffected College Groups: Logged Results 190
Table 3.A3. CITS Results with High- and Low-Pell Groups: Logged Results 191

Paper 1: District Apportionment in the California Community College System

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Abstract

The California Community College (CCC) system has long been funded by an enrollment-based funding formula that weights funding equally for all students. The recently-adopted Student-Centered Funding Formula (SCFF) substantially affects district funding allocations by weighting funding more highly for students who are financial aid recipients and who achieve one of several success outcomes. In this paper, I discuss state apportionment funding for the CCC system in detail. I describe how the SCFF affected district funding allocations relative to the prior formula. I also draw on CCC apportionment data in 2017 and 2018 to estimate these changes using ordinary least squares regression modeling. Results show that the SCFF shifted revenue towards districts that serve higher proportions of lower-income students. This increased progressivity in CCC funding relative to the prior formula.

Introduction

The California Community Colleges (CCC) system consists of 116 public colleges. It is part of California's three-tiered public education system which includes the California State University (CSU) and University of California (UC) systems. The CCC system plays an integral role in the state's postsecondary education, precollegiate instruction, and workforce preparation. It also serves as a central component in the pipeline for student enrollment in CSUs and UCs.

The CCC system is publicly funded and the state's funding processes are a crucial determinant of its success. District apportionment, or the state's allocation of funds across districts according to a funding formula, is particularly important. Combined with local property taxes, this revenue finances most of a district's day-to-day operations and is thus essential to a district's educational functions. Over the past few decades, the state has made significant changes to the CCC funding formula which impact district revenue. These reforms have largely aimed to compensate districts for their costs of service in a manner that is both adequate and equitable.

In 2018-19, the state implemented the Student-Centered Funding Formula (SCFF) which allocates additional funds to districts that serve low-income students and rewards high-performing districts. It was designed reduce achievement gaps and bolster success among CCC students. The SCFF replaced the Enrollment-Based Funding Formula (EBFF) which funded districts according to their enrollment and eliminated funding disparities across districts. The SCFF thus represents a major shift in the state's funding priorities by introducing increased funding progressivity and a performance-based component to district apportionment.

In this report, I focus on district apportionment in the CCC system and evaluate the funding changes that resulted from the SCFF's adoption. I begin in *CCC Context* by providing an overview of the CCC system's mission, governance, educational offerings, and revenue. In *CCC Revenue Sources*, I discuss state and district budgeting and illustrate the CCC system's various revenue sources. In *Allocating State Revenues across Community College Districts*, I explain how these revenue sources are used to fund a district's entitled apportionment. In *Historical Approaches to California Funding Formulas*, I describe the funding mechanics of the EBFF and SCFF. Finally, in *Evaluating Funding Changes under the SCFF*, I examine how the shift from the EBFF to the SCFF affected district apportionment outcomes. I describe how funding changes are associated with district size, minority share, and student income. Finally, I illustrate the relationship between district funding and student income in the EBFF and SCFF.

I find that the SCFF allocated the largest funding gains to low-income districts as intended. This strengthened the negative association between district funding and student income, thereby increasing progressivity in formula funding.

CCC Background

The CCC system's educational mission is multi-faceted. Its primarily offers academic and vocational instruction for students of all ages through the second year of college (Comprehensive Mission Statement, 1976). It also offers precollegiate instruction to help students succeed at the postsecondary level and workforce development services to teach students skills that are demanded by their regional economies. Finally, the CCC system's credential offerings include associate degrees, certificates[1], and

[1] Certificate programs often support students who are completing their GED, learning English as a second language, preparing for citizenship, preparing to enter the workforce (e.g. career and technical education programs), and seeking to improve life skills (e.g. parenting skills courses) (Aschenbach & Young, 2016; CCCCO, 2021c; Ton-Quinlivan, 2019). Certificates vary in length and are typically require fewer units than a degree.

Associate Degrees for Transfer[2] (ADTs) (CCCCO, 2021b). Each of these is offered in arts and science and across hundreds of subfields.

CCC system's scale is massive—It consists of 73 districts and 116 colleges (California Department of Finance, 2021). It serves more than two million students annually, or roughly one in every four community college students in the United States, making it nation's largest higher education system. In 2019-20, it awarded 196,000 degrees and 115,000 certificates while transferring 107,000 students to four-year institutions (CCCCO, 2021d). These transfer students represent an impressive share of baccalaureate earners in California. Nearly one-third of UC graduates and over half of CSU graduates begin their postsecondary education in the CCC system.

CCC districts and colleges are overseen by the Board of Governors and a board-appointed chancellor (Smith, 2018). The California Community College Chancellor's Office (CCCCO) is responsible for allocating state revenue to districts and also plays an important role in communicating districts' financial needs to the board and state. CCC districts are governed by a board of trustees and a CEO who are responsible for developing a budget within state-set parameters that meets its local educational needs.

CCC revenue per student is quite low compared to the CSU and UC systems as well as community colleges in other states. Its revenue per Full Time Equivalent Student[3] (FTES) is less than half the rate of CSUs and less than a quarter of the rate of UCs (Community College League of California, 2019). Further, in the 2010-2018 period,

[2] ADT recipients are guaranteed admission to the California State University (CSU) system and may transfer their credits towards a CSU bachelor's degree with a similar curricular focus (Wheelhouse, 2017).
[3] FTES measures enrollment by student instruction hours (Mullen, 2020; T. M. Scott, 2017). One FTES is equivalent to 525 instruction hours, the estimated instructional hours for a typical full-time student.

California's public, 2-year institutions[4] ranked an average 31st in revenue per FTES[5] out of 47 states with available data (National Center for Education Statistics, 2021).

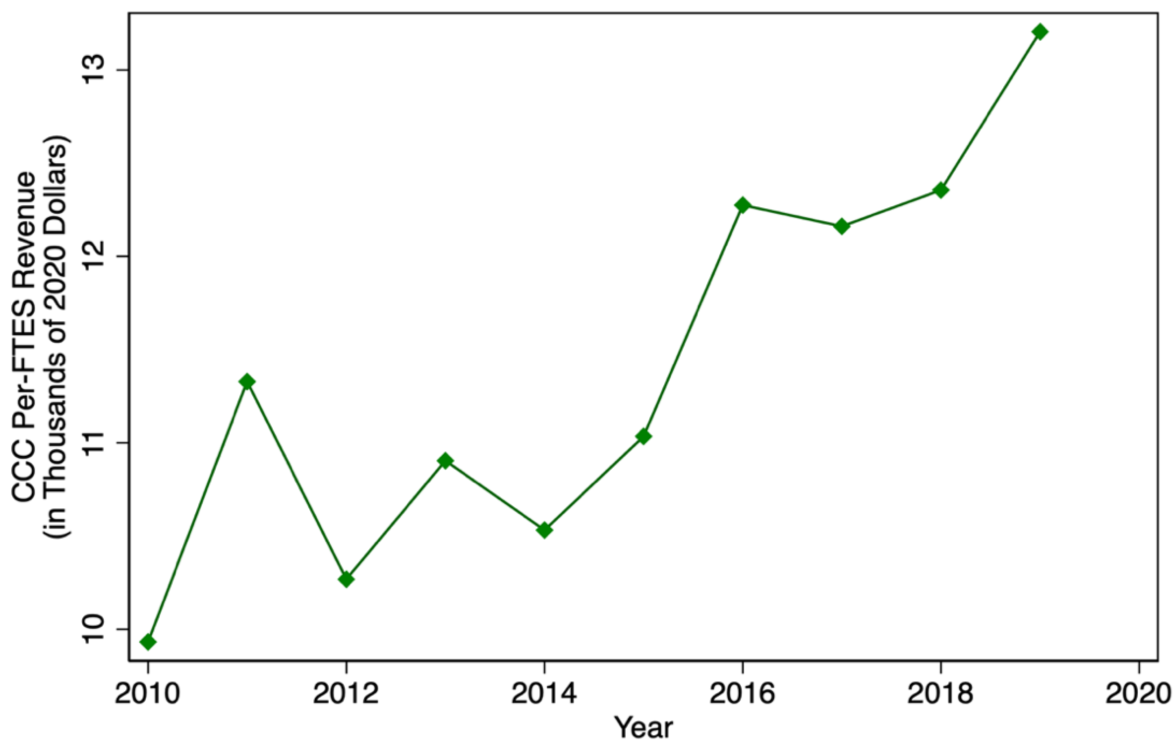
Over the past decade, CCC revenue has been volatile but overall increasing. Figure 1 illustrates this trend for 2010-2019[6]. In the early 2010s, the state was forced to make large budget cuts in the aftermath of the Great Recession (Mullen & Justice, 2018; Smith, 2018). This resulted in sharp declines in per-FTES funding rates in the 2010-2014 period. However, the state restored this reduction in the subsequent years and ultimately increased funding beyond its pre-decline levels. From 2010 to 2019, per-FTES funding increased by more than 30 percent after inflation.

[4] This sample is primarily but not entirely comprised by CCCs and thus represents a strong representation of CCC revenue.

[5] I compute a state's revenue per FTES using IPEDS data as its average total revenue divided by its average FTES among 2-year colleges in the same year. For instance, I divide 2018 fiscal year revenue by 2017-18 FTES.

[6] Revenue data is not available for years before 2010. Thus, I display revenue trends for the 2010s in Figure 1 but show enrollment trends for 2000-2019 in Figure 2 below.

Figure 1.1. CCC Revenue per FTES 2010-2019

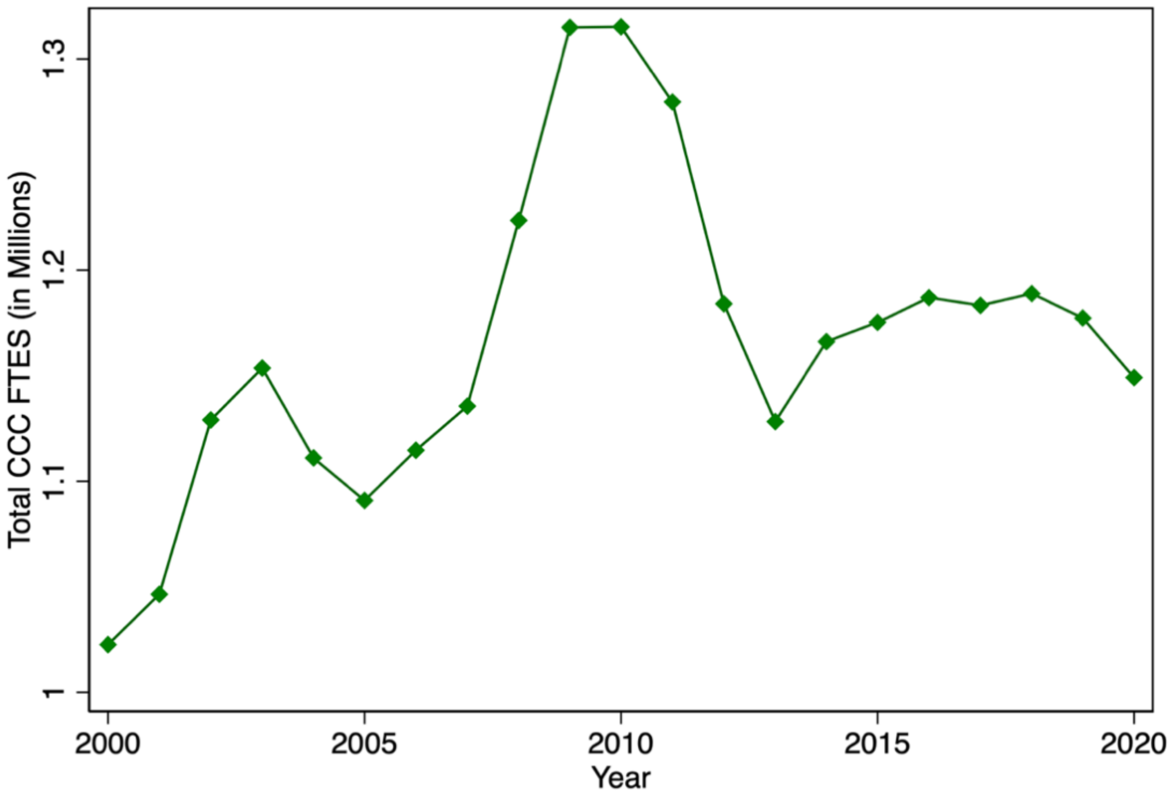


Notes: Sources include CCCCO Management Information Systems Data Mart, "Full-Time Equivalent Students (FTES) Counts", and CCCCO CCFS-311 Reports, "Summary of Financial Transactions by Fund." The revenue measure in this figure sums CCC revenue across all district budget funding sources for each district. Annual revenue is converted to constant 2020 dollars using the Consumer Price Index reported by the Bureau of Labor Statistics.

CCC FTES demonstrates a similarly volatile pattern over the past two decades. Figure 2 demonstrates this trend for 2000-2020. Enrollment peaked in the years following the Great Recession. However, in the early 2010s, enrollment declined to its pre-Recession level and afterwards grew at a moderate pace. Toward the end of the 2010s, enrollment was stagnant. Finally, enrollment declined in 2020 resulting from the Covid-19 pandemic[7] (Burke, 2020).

[7] 2020 FTES records enrollment in July 2019 through June 2020. Thus, Figure 2 captures only part of the Covid-19 effect as the pandemic interrupted only the final third of this enrollment period.

Figure 1.2. CCC FTES 2000-2020



Source: CCCCO Management Information Systems Data Mart, "Full-Time Equivalent Students (FTES) Counts"

CCC Revenue Sources

Apportionment revenue is essential to CCC finance. It funds a district's day-to-day operations and is unique relative to other revenue sources in that it may be spent in a largely discretionary manner. In this section, I explain and illustrate the various sources of revenue that compose a district's budget in order to highlight the significance of apportionment revenue. Further, I discuss how total apportionment funds are appropriated by the state.

District Budgeting and the General Fund

A district's budget is composed of a few dozen funds (CCCCO, 2012). These contain varied sources of revenue which have unique accounting rules and spending restrictions. For instance, a district receives financial aid revenue from the federal government which it must hold in a trust for student recipients. In Appendix A, I describe each type of district fund and in Figure A1, I illustrate the amount of revenue it holds as a proportion of total CCC revenue.

Here, I focus only on the district General Fund because it contains apportionment revenue and finances a district's primary educational functions (CCCCO, 2012). The General Fund is the largest district fund which made up about 70 percent of total CCC revenue in 2018-19 (CCCCO, 2021c). The General Fund can be broken down into Restricted (20 percent) and Unrestricted (80 percent) sub-funds (CCCCO, 2012). The Restricted General Fund is made up of revenue designated for specific categorical programs with externally-set spending restrictions. For instance, the state allocates restricted revenues for programs such as Veterans Education and Disabled Students Programs and Services which districts may only spend on these respective programs. The Unrestricted General Fund is comprised of discretionary revenues including apportionment revenue (Hartnell Community College District, 2019). Districts must still comply with state standards in spending this unrestricted revenue (T. M. Scott, 2017). For instance, they must spend at least half of this revenue on classroom instruction.

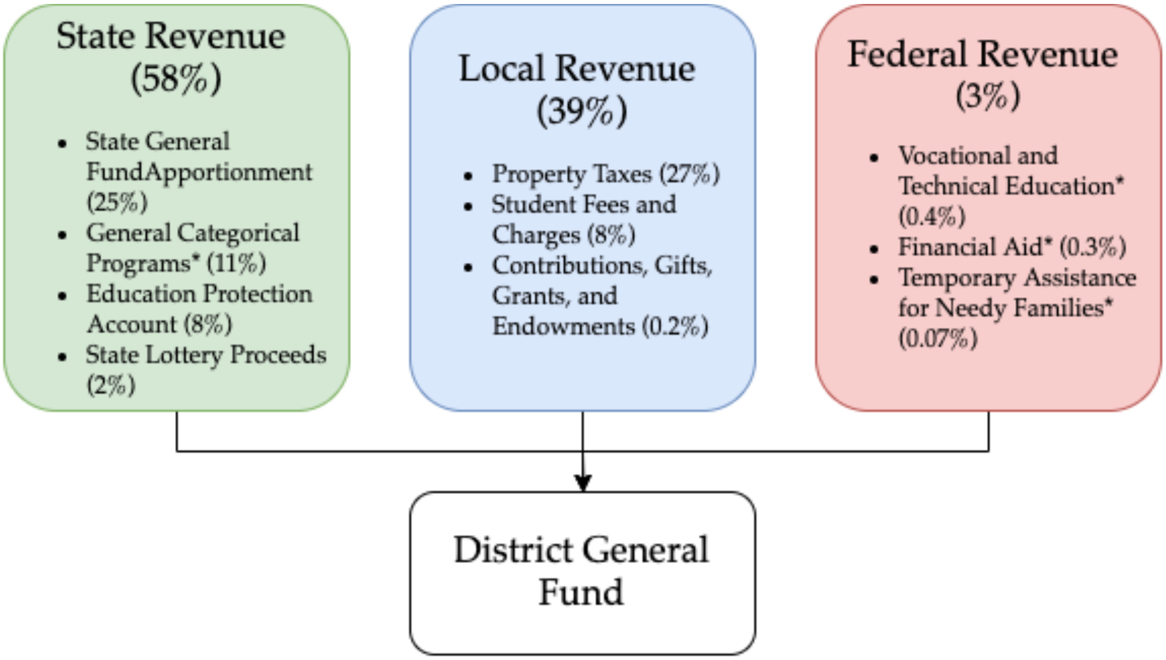
District General Fund Revenue Sources

A district's General Fund is composed of state, local, and federal revenue sources (CCCCO, 2012). Figure 3 illustrates the average share of each of these revenue sources and several prominent sub-sources across CCC districts in 2018-19. Most of a district's General Fund revenue is sourced by the state at an average 58 percent (CCCCO, 2021a). The largest sub-source of state funding is the State General Fund Apportionment[8] (25 percent of a district's General Fund, on average) which provides apportionment revenue allocated by a funding formula[9] (CCCCO, 2012). The next largest component is General Categorical Programs (11 percent) which is comprised of restricted revenues for student support services.

[8] The "General Fund" referred to in the "State General Fund Apportionment" is the state's General Fund, not a district's. I introduce the State General Fund and define the Apportionment more clearly later in this report.

[9] I often use "apportionment revenue" in this report to denote revenue held in this fund. While the state makes other apportionments, I do not review them in detail in this report because they are quite small and allocated under terms set outside the funding formula.

Figure 1.3. CCC District General Fund Revenue Sources



Notes: (*) Denotes a revenue source comprised of primarily restricted revenue. Reported percentages are computed from the CCCCO's CCFS-311 *Summary of General Fund Revenues* and *General Fund Revenue by Source* reports. Each percentage measures the revenue share of a given source relative to a district's total 2018-19 General Fund, averaged across CCC districts. Sampled districts include each operational district except Calbright, an online-only college whose revenue is not directly comparable to that of other districts. Listed revenue sub-sources are not exhaustive within local, state, and federal categories and thus do not sum to 100%. CCCCO (2020, 2012) provides the categorization of individual revenues into sub-funds and of restricted/unrestricted sources. General Categorical Programs include the revenue sources of Child Development, Extended Opportunity Program Services, Disabled Students Programs and Services, Temporary Assistance for Needy Families, CalWORKs, Telecommunications and Technology Infrastructure Program, and Other General Categorical Programs. Property Taxes include Secured, Supplemented, Unsecured, and Prior Year Property Taxes as well as the Education Revenue Augmentation Fund. Student Fees and Charges include Child Development Services, Community Service Classes, Dormitory Fees, Enrollment Fees, Field Trips, Health Services, Instructional Materials Fees, Insurance, Student Records, Non-Resident Tuition, Parking and Public Transportation, and Other Student Fees.

The state also allocates smaller portions of revenue through the Education Protection Account (11 percent) and State Lottery Proceeds (2 percent) (CCCCO, 2012). The Account was created in 2012 by Proposition 30 to supplement district apportionment revenue with new tax revenue generated by its enacting legislation (CCCCO, 2012; Hartnell Community College District, 2019). Its revenue differs from that of the State General Fund Apportionment in that it is not subject to Legislative cuts

(Hartnell Community College District, 2019). State Lottery Proceeds provides districts with both restricted and unrestricted revenues (CCCCO, 2012).

Local revenue represents an average 39 percent of a district's General Fund and consists mostly of unrestricted revenue. Districts primarily raise local revenue through Property Taxes (27 percent) and Student Fees and Charges (8 percent) while a smaller portion comes from sources such as Contributions, Gifts, Grants, and Endowments (0.2 percent) (CCCCO, 2021a). Property tax revenue represents the vast majority of a district's local revenue on average but varies significantly by the size its property tax base. For instance, property tax revenue made up as little as six percent of Citrus Community College District's General Fund but as much as 75 percent of Marin Community College District's General Fund in 2018-19. Districts such as Marin that generate a large portion of their revenue locally are known as "Community-Supported[10]", which I define more precisely below.

Student Fees and Charges include student enrollment fees[11] and non-resident tuition as well as other fees for district operations (e.g., dormitories and health services). Enrollment fees are set by the Legislature at a uniform rate across districts and colleges whereas non-resident tuition is set at the district-level (Smith, 2006). They are incredibly low relative to CSUs and UCs[12] (Savidge, 2018) as well as community colleges in other states (Gordon, 2017). This results in broader student access to the CCC system but

[10] Community-Supported districts are also referred to as "Basic Aid" districts (Legislative Analyst's Office, 2011).

[11] CCC resident student tuition is referred to as "student enrollment fees". Any student who is physically present in the state and intends to make California a permanent home qualifies as a resident (CCCCO, 2001).

[12] In 2018, the cost of full-time, in-state tuition for the CCC system was about $1,100 (Savidge, 2018). This was less than one-fifth the cost of attending a CSU and less than one-twelfth the cost of attending a UC.

lower levels of local district revenue. What's more, roughly half of CCC students pay no student fees resulting from the College Promise Grant and other grants (Savidge, 2018).

Federal revenue represents the final 3 percent of a district's General Fund. These primarily consist of restricted funds for categorical programs such as Career and Technical Education and Temporary Assistance for Needy Families (CCCCO, 2012; Hartnell Community College District, 2019). These revenues are allocated according to federally-set guidelines but are typically allocated by state agencies (Smith, 2018).

State Budgeting under Proposition 98

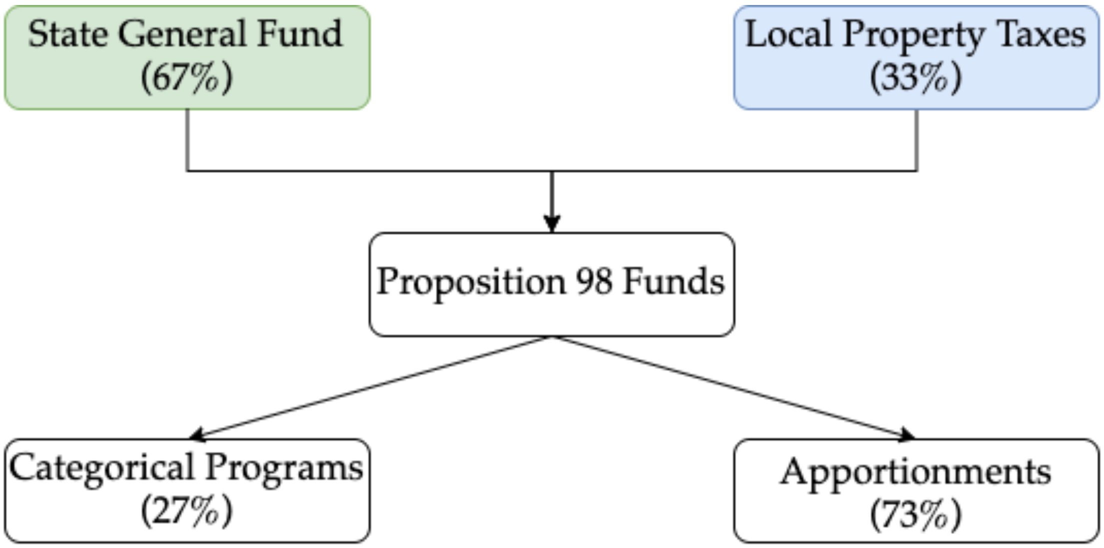
The state is primarily responsible for determining district funding levels (Smith, 2006, 2018). This authority was established with the passage of Proposition 13 in 1978, before which districts raised a majority of their funds through local property tax revenue (Jaschik, 2006). Prop 13 reduced property taxes and removed most taxing authority from local district governing boards, thereby shifting the primary responsibility for financing the CCC system and other systems to the state (Jaschik, 2006; Murphy, 2004; Smith, 2006).

The vast majority of the state's CCC revenue is made up of Proposition 98 funds[13] (Petek, 2020). Illustrated in Figure 4, these funds are sourced from both the State General Fund[14] and local property taxes. The state allocates these funds towards district apportionments, primarily the State General Fund Apportionment, and categorical

[13] The state also allocates a smaller amount of revenue from funds such as the Education Protection Account and State Lottery Proceeds (Petek, 2020) which do not fall within Prop 98 (CCCCO, 2020a; Hartnell Community College District, 2019).
[14] The State General Fund serves a similar purpose as a district's General Fund. It is the state's primary operating account which contains revenue that may be spent with few restrictions (Graves, 2014). It finances public services including CCC, K-12 schools, CalWORKs, and infrastructure.

programs. These manner in which these funds are allocated to districts are set by state budgeting processes outside the Prop 98 framework (T. M. Scott, 2017).

Figure 1.4. CCC Proposition 98 Funds Sources and Allocations



Notes: Each reported percentage is estimated using 2018-19 budget data. The proportion of Proposition 98 funds estimated from the State General Fund and local property taxes are estimated from Legislative Analyst's Office (2019). The proportion of Proposition 98 funds that is used for categorical and apportionment funding is estimated from Petek (2020).

Prop 98 was passed in 1988 and establishes a framework under which the Legislature determines an annual funding level for K-14 education (primarily K-12 and CCC), known as the "minimum guarantee" (Kappahn & Kuhn, 2017; T. M. Scott, 2016). It was designed to keep this funding level at pace with enrollment growth and inflation. Its provisions, along with subsequent propositions and legislation, define three mutually exclusive tests which the Legislature may use to determine the minimum guarantee:

- Test 1—The guarantee is set at roughly 40 percent of the State General Fund.
- Test 2—The guarantee is set at the prior year's funding level, adjusted for changes in student attendance and inflation.

- Test 3—The guarantee is set at a lower level than under Tests 1 or 2 if State General Fund growth is weak (Kappahn & Kuhn, 2017; T. M. Scott, 2016).

The state also uses several provisions to maintain stability in the minimum guarantee over time. For instance, if the Legislature provides a lower funding level with Test 3, it essentially creates an IOU equal to the revenue reduction which must be restored in years with strong General Fund growth (Kappahn & Kuhn, 2017; T. M. Scott, 2016). Additionally, spikes in General Fund revenue which cause large increases in the minimum guarantee are not carried forward to the state's funding obligation in future years (Kappahn & Kuhn, 2017). Finally, the School Stabilization Account smooths revenue over years with strong and weak General Fund revenue to help the state meet its funding commitment each year.

Next, the Legislature splits the minimum guarantee between the CCC system and K-12 schools (T. M. Scott, 2017). While a statute requires the state to allocate at least 10.9 percent of the minimum guarantee to the CCC system annually, the Legislature may suspend this provision in any given year (Community College League of California, 2017; Murphy, 2004; T. M. Scott, 2016). From 2004-05 to 2017-18, the CCC system received a state appropriation ranging from 10.04 percent to 12.14 percent of the minimum guarantee (Community College League of California, 2017).

All in all, this legislative framework has succeeded in providing the CCC system with funding levels that have kept pace with enrollment growth and inflation over a long time horizon (Petek, 2020). At the time of this report, funding rates are at an all-time high and have grown by roughly 30 percent above inflation over the past three decades. However, year-to-year funding changes have shown significant volatility resulting from business-cycle swings.

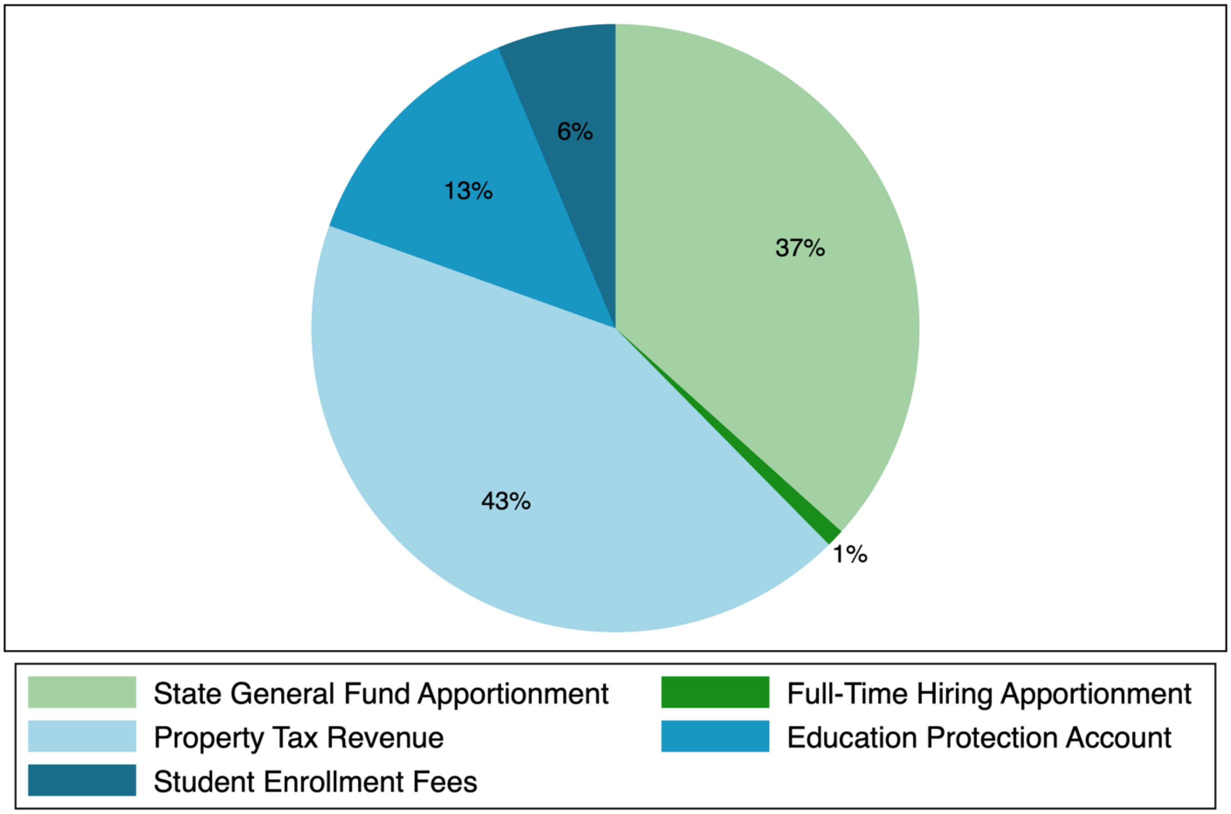
Allocating State Revenues across Community College Districts

The CCCCO is responsible for fulfilling a district's annual apportionment as computed by a funding formula. It refers to this calculated apportionment as "Total Computational Revenue" (TCR). In this section, I describe how the CCCCO uses various revenue sources to fulfill TCR but do not yet discuss how TCR is computed. I save this discussion for the following section.

The CCCCO uses a combination of local and state revenue sources to fund TCR. Figure 5 illustrates the composition of 2018-19 total TCR by revenue source. Local revenues include Property Tax Revenue (43 percent of total CCC TCR) and Student Enrollment Fees (6 percent). State revenues include the State General Fund Apportionment (37 percent), the Education Protection Account (13 percent), and the Full-Time Hiring Apportionment[15] (1 percent).

[15] The Full-Time Hiring Apportionment was created by the 2015-16 Budget Act to incentivize districts' full-time faculty hires (Mullen & Justice, 2018).

Figure 1.5. CCC TCR by Revenue Source



Notes: Reported percentages represent the corresponding revenue source summed across districts and divided by total CCC TCR in 2018-19. Sampled districts include each operational district except Calbright, an online-only college whose revenue is not directly comparable to that of other districts. Estimates are obtained from the CCCCO's 2018-19 Recalculation Apportionment.

The manner in which the CCCCO uses these revenue sources to fulfill district TCR is nuanced[16]. It first allocates each source except for the State General Fund Apportionment to every district (Mullen & Justice, 2018). I call the sum of these sources "communal revenue". For most districts, TCR cannot be fulfilled with communal revenue alone. Thus, the CCCCO subsequently uses the State General Fund Apportionment to fund the remaining TCR for these districts. For a small number of

[16] I describe the procedures for TCR funding that are currently used at the time of this report. Some components of current TCR funding will not apply for the earlier funding years. For instance, the Education Protection Account was established in 2012 and was previously not available to fund TCR (Hartnell Community College District, 2019).

Community-Supported districts[17], TCR can be achieved with communal revenue alone, driven by high property tax revenue. Thus, these districts do not receive any revenue from the State General Fund Apportionment.

Table 1 illustrates this sequence of steps using 2018-19 CCCCO apportionment data for two districts: Riverside, which is not Community-Supported, and Marin, which is. First, the CCCCO calculates each district's communal revenue as the sum of its Property Tax Revenue, Student Enrollment Fees[18], Education Protection Account[19], and Full-Time Hiring Apportionment (CCCCO, 2020b). It deducts this communal revenue from each district's TCR to form a remaining TCR balance. Note that Riverside has a small amount of tax revenue relative to its TCR and thus a large remaining balance whereas Marin's tax revenue exceeds its TCR and thus has and no remaining balance. Thus, Marin qualifies for Community-Supported status whereas Riverside does not.

[17] Historically, only three districts with high levels of property wealth were consistently designated as Community-Supported (Murphy, 2004; Smith, 2018). However, following state funding cuts in the early 2010s, district TCR fell which made this status more easily attainable. Using CCCCO Apportionment Recalculation data, I find that there were eight Community-Supported districts in 2018-19.
[18] Only 98 percent of a district's student fees revenue is applied to its TCR. Murphy (2004) remarks that the state's rationale for deducting 98 percent rather than 100 percent is unclear.
[19] Account funds are allocated using per-FTES rates that vary across districts (CCCCO, 2019c). Community-Supported districts receive lower rates than other districts.

Table 1.1. Total Computational Revenue and Apportioned Revenue in Practice

	Revenue Type (Calculation)	Riverside (Non-Community-Supported)	Marin (Community-Supported)
1	**2018-19 Total Computational Revenue (TCR)**	**$190,657,655**	**$26,300,833**
2	Property Tax Revenue	$49,627,813	$57,971,273
3	Student Enrollment Fees	$10,497,134	$1,966,700
4	Education Protection Account	$28,524,033	$341,205
5	Full-Time Faculty Hiring Apportionment	$1,724,252	$221,306
6	Communal Revenue (2+3+4+5)	$90,373,232	$60,500,484
7	Remaining TCR (1-6 if difference is positive, $0 otherwise)	$100,284,423	$0
8	State General Fund Apportionment (7-10)	$100,163,583	$0
9	**Apportionment** (6+8)	**$190,536,815**	**$60,500,484**
10	Revenue Deficit (1-9)	$120,840	$0

Notes: TCR (1) is the amount of a district's formula-computed entitlement whereas Apportionment (9) is the amount of its received revenue. Each district's Apportionment (9) equals the sum of Communal Revenue (6) and State General Fund Apportionment (8). For a non-Community-Supported district, Apportionment (9) is either equal to TCR (1) with no deficit or less than TCR by the amount of a Revenue Deficit (10) if one exists. For a Community-Supported district, Apportionment (9) meets or exceeds TCR (1). Because its Communal Revenue (6) alone meets or exceeds TCR (1), it receives no State General Fund Apportionment (8) or Revenue Deficit (10). Data for this table is sourced from the CCCO's 2018-19 Recalculation Apportionment June 2020 revision.

Next, the CCCCO uses the State General Fund Apportionment to fulfill the remaining TCR balance for Riverside only. For years in which state-appropriated revenue is insufficient to fulfill the remaining TCR balance for all districts, the CCCCO applies a revenue deficit. This value equals the difference between a district’s TCR and actual apportionment revenue. In 2018-19, the CCCCO applied a small deficit for Riverside.

In sum, a Community-Supported district’s annual apportionment is composed of communal revenue only. A non-Community-Supported district’s apportionment is composed of communal revenue plus the State General Fund Apportionment which may include a revenue deficit. This funding process effectively uses a district’s local revenue to offset the state’s funding obligation for TCR. Because each district retains its full tax revenue in its apportionment, a Community-Supported district may generate apportionment funds that far exceed its TCR. In the example above, Marin raises more than twice the revenue provided by its TCR. However, the use of the State General Fund Apportionment helps mitigate funding disparities as districts with lower levels of local revenue receive a disproportionate amount of apportionment funds (Murphy, 2004).

Historical Approaches to California Funding Formulas

The CCCCO uses a state-legislated funding formula to compute a district's TCR each year (Smith, 2018). Historically, the state has designed funding formulas to compensate districts for their educational costs using workload measures and corresponding funding rates (Murphy, 2004). These workload measures allow district services to be quantified. For instance, district FTES, number of campuses, and number of degrees awarded have been included in past and present funding formulas.

Over the past few decades, the state has used three distinct funding formulas for district apportionment: the Program-Based Funding Formula (PBFF) in 1991-92 through 2005-06, the Enrollment-Based Funding Formula[20] (EBFF) in 2006-07 through 2017-18, and the Student-Centered Funding Formula (SCFF) in 2018-19 through present. Each formula varies considerably in its funding components and principles. The PBFF funded districts according to the cost of delivering services at a particular standard (Murphy, 2004). However, this policy was highly intricate as it used several distinct workload measures and funded these measures at varying rates across districts. The

[20] This formula may be referred to by its enacting legislation, Senate Bill 361 (T. M. Scott, 2017). I use "enrollment-based" to refer to the fact that, unlike the PBFF and SCFF, the EBFF apportions revenue almost exclusively according to FTES.

EBFF was designed to simplify this funding process by establishing FTES as its sole workload measure and implementing equalized (invariant) funding across districts. Finally, the SCFF retained the funding components of the EBFF while adding components that allocate additional revenue to low-income and high-performing districts.

Below, I discuss the EBFF and SCFF in detail to provide context for my evaluation of apportionment changes associated with the SCFF. I also provide a brief summary of the PBFF in Appendix B which also receives excellent coverage in Murphy (2004).

Enrollment-Based Funding Formula

The EBFF established a straightforward, equitable system for district apportionment. It improved upon the state's prior PBFF by implementing:

- FTES as its sole workload measure
- equalized marginal FTES funding rates across districts[21]
- increased compensation for economies of scale[22]
- "stability" and "restoration" mechanisms to increase a district's fiscal stability amid enrollment declines (Jaschik, 2006; T. M. Scott, 2017).

Under the EBFF, a district's apportionment is computed as the sum of two main funding components. The first of these is the "basic allocation", a lump sum payment which primarily compensates a district for its scale as measured by its FTES and

[21] EBFF rates were not completely equalized across districts (C. Osmena, personal communication, April 8, 2021). The legislature set increased rates for ten districts to prevent them from experiencing losses relative to the PBFF.
[22] That is, that a large district's costs per student tend to be lower than that of a small district (Griffith, 2017)

number of colleges (Base Fiscal Year Revenues, 2011). The second measure, which I call "instructional revenue"[23], which funds three types of instruction at distinct marginal funding rates. The sum of these equal district TCR under this formula.

Basic Allocation

A district's basic allocation is a function of its number of colleges and education centers[24] and prior year FTES recorded for each college or center (Base Fiscal Year Revenues, 2011; T. M. Scott, 2016; Smith, 2018). Per-college and per-center rates are determined by a schedule which provides higher rates for single-college districts to compensate for economies of scale. Further, rural colleges[25] are eligible per-college rate premium under the Rural College Access Grant (Smith, 2018).

Table 2 displays the basic allocation schedule for 2006-07. A district earns the summed rates for each of its colleges and education centers. For instance, a district containing two non-rural colleges, one with 25,000 FTES and another with 15,000 FTES, and no education centers would receive a basic allocation of $7.5 million in this funding year.

[23] This may also be referred to as "FTES Revenue" by the state.
[24] Education centers are district campus sites with lower FTES than colleges. Campus sites must have at least 500 FTES to be recognized as an education center but must have at least 1,000 FTES to be eligible for a basic allocation rate (Base Fiscal Year Revenues, 2011; T. M. Scott, 2016, 2017). However, centers with fewer than 1,000 FTES that existed before implementation of EBFF are "grandparented" in to the policy and eligible for a basic allocation rate.
[25] Colleges and centers in single-college districts with fewer than 5,000 credit FTES and a population density less than half the statewide average are eligible for this "rural" designation (*SB 361 (Scott)/Community Colleges Funding Formula Reform*, 2006).

Table 1.2. Basic Allocation Schedule in 2006-07

FTES Level	Rate per College for Single-College Districts	Rate per College for Multi-College Districts	Rate per Education Center
FTES ≥ 20,000	\$5,000,000†	\$4,000,000†	--
10,000≤ FTES <20,000	\$4,000,000†	\$3,500,000†	--
FTES < 10,000	\$3,000,000†	\$3,000,000†	--
FTES ≥ 1,000	--	--	\$1,000,000
750 ≤ FTES < 1,000	--	--	\$750,000*
500 ≤ FTES < 750	--	--	\$500,000*
250 ≤ FTES < 500	--	--	\$250,000*
100 ≤ FTES < 250	--	--	\$125,000*

Notes: (†) Denotes rates that increase by \$500,000 for rural colleges. (*) Denotes rates that are only eligible for "grandparented" education centers, those that existed prior the the EBFF's implementation. Reported rates are obtained from Base Fiscal Year Revenues, 58771 California Code of Regulations § Title 5 (2011).

Instructional Revenue

Next, the EBFF apportions revenue for three types of instruction:

- Credit—These courses align with a district's recommended curriculum for an associate degree (Standards and Criteria for Courses, 2019). These must be graded and meet a requisite level of academic intensity.
- Noncredit—These courses offer free enrollment for students and do not count towards associate degree completion (Aschenbach & Young, 2016). They often support students who are non-native English speakers, precollegiate learners, preparing for citizenship, preparing to enter the workforce, or seeking to improve life skills.
- Career Development and College Preparation (CDCP)—The CDCP program was created by the EBFF's enacting legislation to provide additional funding for

applicable noncredit courses. CDCP courses emphasize vocational and precollegiate training through noncredit certificate programs (Aschenbach & Young, 2016; Los Angeles City College, 2021). Programs are offered in the areas of basic skills (e.g. High School Equivalency Test Preparation), English as a second language, short-term vocational training (e.g. Custodial Technician Training), and workforce preparation (e.g. Workforce Literacy Skills).

A district's instructional revenue equals the sum of its prior year FTES in each instruction type multiplied by the respective current year funding rates[26]. In the EBFF's first operational year, per-FTES funding rates[27] were set at $4,367 for credit, $2,626 for noncredit, and $3,092 for CDCP instruction (Community Colleges Funding, 2006). Since credit instruction makes up roughly 95 percent of total CCC FTES (Aschenbach & Young, 2016) and was funded at the highest rate for much of the duration of the EBFF, credit instructional funding was the primary driver of EBFF apportionment.

Base Revenue

Before reviewing the remaining funding mechanisms of the EBFF, it is useful to introduce a couple key terms. First, "base FTES" denotes a districts prior year funded FTES (Base Fiscal Year Revenues, 2011). A district's base FTES may differ from its actual FTES in the prior year because it may contain funded and unfunded FTES[28]. The CCCCO computes a district's current year revenue using its base FTES. Thus, current

[26] However, the state caps the amount by which each FTES may grow in a given year. I discuss these in detail in Appendix C.
[27] The legislature adjusts these rates over time for various reasons. For instance, in 2015-16, the Legislature provided began funding CDCP fully by setting its marginal rate equal to the credit rate (Smith, 2018). These rates also may be adjusted upwards or downwards depending on the state's budget condition.
[28] I explain why a district may have unfunded FTES in Appendix C.

year revenue is referred to as "base revenue". Under the EBFF, base revenue equals the sum of the basic allocation and instructional revenue. In equation form, this is:

$$(1)\ EBFF\ Base\ Revenue = Basic\ Allocation + Base\ Credit\ FTES * \ Credit\ Rate + Base\ Noncredit\ FTES * Noncredit\ Rate + Base\ CDCP\ FTES * CDCP\ Rate$$

Inflation Funding

Inflation funds compensate districts for their increased cost of services. The state sets a single cost of living adjustment (COLA) rate[29] for the CCC system and budgets the amount of Prop 98 funds required to scale systemwide base revenue by that rate (Petek, 2020). The CCCCO uses this rate to proportionally scale each district's base revenue (Inflation Adjustments, 2007). Thus, a district's inflation revenue is equal to its base revenue multiplied by the COLA rate.

Additional EBFF Mechanisms

The EBFF also included provisions for growth, stability, and restoration funding. These guide districts in managing their enrollment levels over time and offer protection against revenue losses resulting from FTES declines. I cover these mechanisms in detail in Appendix C. Note that these are largely unchanged across the EBFF and SCFF so I do not discuss them in the following section.

[29] The state's budgeted COLA rate was volatile over the EBFF's operational period. It was set at roughly five percent in the years preceding the Great Recession, zero in the years following the Recession, and one percent in the final few years of the EBFF (T. M. Scott, 2017)

Student-Centered Funding Formula

In 2018-19, the Legislature adopted a new formula known as the "Student-Centered Funding Formula" (SCFF) which replaced the EBFF (Program-Based Funding, 2020). This policy change was motivated by a broader call for CCC reform across state agencies. These reforms were articulated in the 2017 *Vision for Success* which outlines the CCC system's contemporary challenges and inefficiencies along with corresponding performance benchmarks. It calls on the CCC system to:

1. Raise the rates of degree and certificate completion
2. Raise the rate of transfer to a CSU or UC
3. Reduce average duration of degree completion in terms of both time and accumulated units
4. Raise the rate of Career and Technical Education (CTE) students who enter the workforce in a relevant field
5. Reduce the gaps in the preceding outcomes across student race
6. Reduce the gaps in the preceding outcomes across regional income and educational attainment levels (Foundation for California Community Colleges, 2017).

Since the EBFF only apportioned revenue on the basis of FTES, it did not provide incentives for districts to improve upon these metrics (Legislative Analyst's Office, 2018). Thus, the state implemented the SCFF to better align a district's financial incentives with the *Vision for Success* (CCCCO, 2020c). The formula adopted new workload measures to pay districts for their performance on each of the goals listed above. These include the "supplemental allocation" which pays a district according to its number of enrolled of financial aid recipients and the "student success allocation" which pays a district according to its enrolled students who achieve one of eight different outcomes. The SCFF also retained the EBFF's basic allocation and instructional revenue. Collectively, these components form district TCR under the SCFF.

While the state increased funding levels to finance the SCFF[30], these new allocations do not represent across-the-board funding increases to districts. Rather, the state considerably reduced the marginal credit FTES rate—the primary driver of district revenue under the EBFF—in the SCFF. This offset some of the increase in expenditure resulting from the added allocations.

Basic Allocation

The basic allocation schedule and computation method were unchanged by the SCFF (CCCCO, 2019a, 2020c).

Instructional Revenue

The SCFF modified the EBFF's computation of instructional revenue in a few primary ways. First, it replaced the base credit FTES measure with a three-year rolling average[31] measure in order to improve district revenue stability (CCCCO, 2019a, 2020c; Program-Based Funding, 2020). However, each other SCFF FTES measure retains the base FTES measure from the EBFF. Further, it added two new credit FTES workload measures for special admit[32] and incarcerated students (CCCCO, 2020c). Finally, it

[30] For instance, the state's increased its General Fund appropriation by about $300 per student between 2017-18, the last operational year of the EBFF, and 2018-19, the first operational year of the SCFF (Petek, 2019). By comparison, the increase in the preceding two years was $20 and $140, respectively. Thus, while increased state support for the SCFF was substantial, it was not dramatically higher than in prior years.
[31] For instance, credit revenue in 2018-19 was apportioned according to a district's average credit FTES in the 2016-17 to 2018-19 period (Program-Based Funding, 2020).
[32] Special admit students are high school students who are deemed eligible for "advanced scholastic or vocational work" by their K-12 district (Rustan, 2019).

reduced the credit FTES funding rate by about 30 percent (CCCCO, 2019b, 2020b), thereby reducing the portion of TCR composed of instructional revenue.

Table 3 displays the schedule of marginal FTES rates for 2018-19, the SCFF's first operational year. Special admit, incarcerated, and CDCP instruction are funded at the highest rate of $5,457 while credit and noncredit are funded roughly 30 percent below that at $3,727[33].

Table 1.3. SCFF FTES Funding Schedule in 2018-19

FTES Type	Rate
Credit	$3,727
Special Admit Credit	$5,457
Incarcerated Credit	$5,457
CDCP	$5,457
Noncredit	$3,347

Source: CCCCO 2018-19 Recalculation Apportionment

Supplemental Allocation

The supplemental allocation aims to reduce the financial barriers to the CCC system among low-income and undocumented students (CCCCO, 2019a). A district's supplemental allocation is computed according to its prior year headcount of low-income and undocumented students (CCCCO, 2020c). In 2018-19, it paid a district $919[34] for each Pell Grant[35] recipient, Promise Grant recipient[36], and AB 540 student[37]

[33] Like the EBFF, the SCFF did not set a perfectly equalized credit rate schedule (C. Osmena, personal communication, April 8, 2021; Program-Based Funding, 2020). The formula sets separate, higher rates for the same ten districts that were awarded higher rates under the EBFF.

[34] This rate was increased to $948 in 2019-20 and adjusted for COLA in each year (Program-Based Funding, 2020).

[35] The Pell Grant covers tuition for a student who demonstrates a requisite level of financial need on their Free Application for Federal Student Aid (Martorell & Friedmann, 2018).

[36] The Promise Grant covers student enrollment fees for low-income students (Martorell & Friedmann, 2018).

[37] AB 540 students qualify for free resident tuition and consist primarily of undocumented students (Petek, 2020).

(CCCCO, 2020b). For instance, assume a district enrolls two students, one of whom is both a Pell and Promise recipient and another who is AB 540. This district would receive a supplemental allocation of $2,757.

Student Success Allocation

The student success allocation provides incentives for eight student outcomes which are aligned with *Vision for Success* (CCCCO, 2019a). Like the supplemental allocation, it supports low-income students by paying a district a premium rate for its number of enrolled Pell and Promise recipients who achieve each outcome.

Table 4 displays the 2018-19 student success allocation schedule. Each outcome corresponds to different point value for all students, Pell students, and Promise students (CCCCO, 2020b; Program-Based Funding, 2020). The allocation uses two per-point rates, a standard rate for all student points and a premium rate for Pell and Promise student points. In 2018-19, this allocation used rates of $440 for all students and $111 for Pell and Promise students[38]. The rate for each outcome is computed as its corresponding point value multiplied by its per-point rate. One student may earn two or three rates if they are a Pell or Promise recipient or both.

In 2018-19, a district's supplemental allocation was determined by its prior year headcount, implying that one student may earn as many rates as outcomes they achieved in a year (CCCCO, 2019a; Program-Based Funding, 2020). For instance, a student who is both a Pell and Promise recipient and earns both an associate degree and certificate in the prior year would earn $3,588[39]. However, in 2019-20, the state replaced

[38] The all student and Pell and Promise rates were increased to $559 and $141 in 2019-20, respectively, and adjusted for COLA in all years (Program-Based Funding, 2020).
[39] I compute this as the all student rate ($440 * [3+2]), plus the Pell rate ($111 * [4.5+3]), plus the Promise rate ($111* [3+2]).

the prior year headcount with a three-year rolling average for each outcome and stipulated that a student may only earn a single rate associated with the highest-point outcome achieved (CCCCO, 2020c, n.d.). Using the preceding example, the district would earn $2,153 for the same student under this new computational method.

Table 1.4. Student Success Allocation Schedule in 2018-19

Outcome	Points	Rate (Points * $)
All Students Schedule ($440 per point)		
Associate degrees for transfer (ADT) granted	4	$1,760
Associate degrees granted (excluding ADTs)	3	$1,320
Baccalaureate degrees granted	3	$1,320
Credit certificates (16+ units) granted	2	$880
Completion of transfer-level mathematics and English courses within first academic year of enrollment	2	$880
Successful transfer to four-year university	1.5	$660
Completion of nine or more CTE units	1	$440
Attainment of regional living wage	1	$440
Pell Grant Students Schedule ($111 per point)		
Associate degrees for transfer (ADT) granted	6	$666
Associate degrees granted (excluding ADTs)	4.5	$500
Baccalaureate degrees granted	4.5	$500
Credit certificates (16+ units) granted	3	$333
Completion of transfer-level mathematics and English courses within first academic year of enrollment	3	$333
Successful transfer to four-year university	2.25	$250
Completion of nine or more CTE units	1.5	$167
Attainment of regional living wage	1.5	$167
Promise Grant Students Schedule ($111 per point)		
Associate degrees for transfer (ADT) granted	4	$444
Associate degrees granted (excluding ADTs)	3	$333
Baccalaureate degrees granted	3	$333
Credit certificates (16+ units) granted	2	$222
Completion of transfer-level mathematics and English courses within first academic year of enrollment	2	$222
Successful transfer to four-year university	1.5	$167
Completion of nine or more CTE units	1	$111
Attainment of regional living wage	1	$111

Source: CCCCO's 2018-19 Recalculation Apportionment.

Base Revenue

A district's SCFF base revenue can be written as:

$$(2)\ SCFF\ Base\ Revenue = Basic\ Allocation + Instructional\ Revenue + Supplemental\ Allocation + Student\ Success\ Allocaiton$$

Here, instructional revenue represents the sum of credit, noncredit, CDCP, special admit credit, and incarcerated credits FTES multiplied by their respective rates (Program-Based Funding, 2020). The SCFF also introduced the new term "base allocation" to denote the sum of the basic allocation and instructional revenue[40]. The Legislature set rates across each SCFF workload measures so that systemwide base revenue would be approximately weighted as follows[41] (CCCCO, 2019a):

$$(3)\ SCFF\ Base\ Revenue = .7 * Base\ Allocation + .2 * Supplemental\ Allocation + .1 * Student\ Success\ Allocation$$

Inflation Funding

The state's process for inflation funding was largely unchanged by the SCFF (CCCCO, 2019a; Program-Based Funding, 2020). The state scheduled a small increase in the credit rate in the second SCFF year in place of a COLA adjustment. However, in subsequent years it will be subject to COLA adjustment.

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[40] I do not use this term elsewhere in this report to avoid confusion with "base revenue" and "basic allocation". However, it is useful here to review the three allocations that compose SCFF base revenue.

[41] The SCFF's enacting legislation scheduled a three-year phase in so that these weights would adjust to 60 percent base, 20 percent supplemental, and 20 percent student success allocation (CCCCO, 2019a). However, the state opted to suspend this provision, thereby maintaining the 70 percent-20 percent-10 percent weighting in future years (Ohlone College, 2021).

Hold Harmless

Importantly, the SCFF added two hold harmless provisions to protect a district against revenue losses if its SCFF-computed TCR fell below its EBFF-computed TCR. First, each district is guaranteed a minimum TCR through 2024-2025[42] that is set at its EBFF-calculated TCR in 2017-18, adjusted for COLA[43] (CCCCO, 2020c; Program-Based Funding, 2020). Further, each district is guaranteed a minimum TCR computed as its credit, noncredit, and CDCP FTES calculated in the current year and multiplied by the respective marginal 2017-18 funding rates and added to its 2017-18 basic allocation. This sum is adjusted for COLA and is not set to expire during the SCFF's operational period.

Evaluating Funding Changes under the SCFF

The SCFF likely affected district TCR unevenly because it replaced a portion of credit FTES funding with the supplemental and student success allocations. That is, it replaced funding that was invariant across districts in per-FTES terms with funding that varied according to a district's rate of financial aid recipients, undocumented students, and student success outcomes. In this section, I explore these effects by modeling a district's change in TCR as a function of its FTES, minority share, and student income. Finally, I illustrate the relationship between district funding and student income before and after the SCFF's adoption.

[42] The SCFF's enacting legislation initially implemented this provision only for the SCFF's first two operational years (Program-Based Funding, 2020). However, the state later extended this provision multiple times (Ohlone College, 2021).
[43] That is, in each year a district uses this provision, its 2017-18 TCR is adjusted by each COLA rate provided after 2017-18 and including the funding year it is used (CCCCO, 2020c).

Sample

I examine TCR changes across 2017-18, the EBFF's final operational year, and 2018-19, the SCFF's first operational year. By comparing revenue across adjacent years, I attempt to isolate the effect of the formula change while holding other time-varying factors constant[44]. My main analytical sample consists of 72 districts. These include all CCC districts and colleges except CalBright, an online-only college with revenue that is not directly comparable to other CCC campuses.

Measures and Data

District Apportionment

To measure district apportionment, I use TCR data reported in the CCCCO's Recalculation Apportionment. This data contains the final estimates of district revenues for a given funding year, including the SCFF's hold harmless provision. I measure TCR-per-FTES using a district's total FTES[45] in the year corresponding to its apportionment[46]. I obtain FTES data in the *FTES Counts* table in the CCCCO Management Information Systems Data Mart[47]. My analysis models TCR in per-FTES terms to permit funding comparisons across districts with varying size. Finally, I estimate the change in TCR-per-FTES associated with the SCFF as the difference between 2017-18 TCR-per-FTES and 2018-19 TCR-per-FTES. I measure this term in constant 2019 dollars by inflating

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[44] For instance, a district's FTES may shift over time, resulting in an adjustment of its basic allocation. I do not want this factor included in my estimated SCFF effects since it is not related to the mechanical funding changes introduced by the formula.

[45] Unlike base FTES, which I describe above, this FTES measure measures the total students served by a district.

[46] Recall that a district's current year TCR is computed based on its prior year FTES. For instance, 2018-19 TCR-per-FTES measures TCR apportioned in 2018-19 divided by 2017-18 FTES. For simplicity, I denote the TCR and FTES years with their funding years which in this case would be 2018-19 TCR and 2018-19 FTES.

2017-18 TCR using Consumer Price Index data reported by the Bureau of Labor Statistics.

There are two primary advantages of measuring apportionment with TCR as opposed to actual revenue. First, TCR excludes any revenue deficit which the state may apply to a non-Community-Supported district's actual revenue. Since this deficit is unrelated to the mechanical funding changes introduced by the SCFF, it is preferable to exclude this variation from the analysis. Second, because TCR is computed in the same manner for Community-Supported and non-Community-Supported districts, this measure permits funding comparisons across all districts. This larger sample ought to lend itself to a more precise estimation of the SCFF's effects.

However, the shortcoming of this measure is that it undercounts actual district revenue for Community-Supported districts. Further, because Community-Supported districts are funded above their entitled funding floor, their actual revenue is unaffected by the SCFF. Thus, their inclusion in the model reduces the relevance of the results to actual district funding. Still, because this analysis focuses on distributional funding properties rather than actual revenue, I choose to model TCR in a full sample of districts.

District Indicators

I use district indicators for FTES, minority share[48], and student income to explore variability in SCFF effects. I measure FTES and minority share in the 2017-18 base year to lessen the SCFF's influence on these indicators[49]. I measure a district's minority share

[48] I include this term to address equity concerns but do not expect that either the EBFF or SCFF differentially affected district funding outcomes by race, net of other factors.
[49] That is, I attempt to exclude any changes in these factors which may results from a district's response to SCFF incentives.

as the proportion of its FTES comprised by Hispanic and African American students. This data is also obtained from the CCCCO Management Information Systems Data Mart.

Since a student income measure is not readily available, I estimate this indicator as follows. First, I obtain 2019 five-year estimates of median household income at the zip code tabulation area (ZCTA) level reported by the American Community Survey (ACS)[50]. I also obtain each college's FTES in 2017-18 and mailing zip code[51] as well as a zip code to ZCTA crosswalk[52]. Because CCC colleges are commuter schools which primarily serve students living close to their campus (Hall & Kazenoff, 2020), a college's zip code ought to provide a reasonable representation of its student residence. Next, I match each college to its ACS-reported median household income using its zip code and the ZCTA crosswalk. Finally, I estimate a district's median household income by taking the average of its colleges' median household income, weighted by college FTES[53]. For single-college districts, this value is simply the median household income associated with the college.

I use this income measure as opposed to the SCFF workload measures of Pell and Promise recipients because financial aid receipt is determined by factors other than student income. For instance, Martorell and Friedman (2018) find that the gap between Pell receipt and eligibility varies considerably across districts. This suggests that district

[50] This variable is top-coded at $250,000.
[51] I obtain college FTES from the CCCCO Management Information Systems Data Service. I obtain addresses from https://www.cccco.edu/Students/Find-a-College/College-Alphabetical-Listing.
[52] I obtain the crosswalk from United Data Systems (UDS) Mapper at https://maps.udsmapper.org/zcta-crosswalk.cfm. It is generated from the 2017 UDS report.
[53] The ACS does not report median household income for three unique ZCTAs associated with a CCC college. One of these is contained in a multi-college district. I impute this district's median household income using FTES weights from its non-missing colleges. The remaining two colleges are contained in single-college districts and are thus dropped from regression models below which control for median household income.

financial aid administration is an important determinant of Pell receipt and that receipt may be an imprecise measure of student income.

Finally, I generate a Community-Supported indicator variable which equals one if a district has higher actual revenue than TCR in either 2017-18 or 2018-19. I flag eight Community-Supported districts in my dataset. I test the robustness of my regression results to the exclusion of these Community-Supported districts.

Descriptive Statistics

Table 5 presents descriptive statistics for each of these measures. In 2018-19, average TCR increased by roughly $4.5 million above inflation relative to 2017-18. FTES decreased by roughly 160 over this same period. These corresponded to an average $430 increase in TCR-per-FTES, a 7 percent increase relative to the base year[54]. Notice that the maximum values of TCR and FTES are about six times as large as their respective averages. These values represent the massive Los Angeles Community College District which skews these variables considerably. Finally, the average household income and minority share are $94,576 and 51 percent, respectively. Unsurprisingly, the range of each of these variables is large as CCC districts span California regions with varying demographics.

[54] This increase includes the state's 2.5 percent COLA funding increase in 2018-19 (Taylor, 2018). Thus, the remaining difference of roughly 4.5 percent can be interpreted as the change in TCR-per-FTES associated with the SCFF.

Table 1.5. District Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min	Max
EBFF Apportionment					
2017-18 TCR (Millions of 2019 dollars)	72	95.41	85.91	13.11	615.24
2017-18 FTES	72	16512.12	14614.07	1679.61	95742.43
2017-18 TCR-per-FTES (2019 dollars)	72	6076.83	812.01	4512.29	8612.71
SCFF Apportionment					
2018-19 TCR (Millions of 2019 dollars)	72	99.98	88.78	14.11	639.39
2018-19 FTES	72	16349.74	14429.84	1448.41	94162.44
2018-19 TCR-per-FTES (2019 dollars)	72	6507.21	1089.41	4045.47	10151.69
Difference in TCR-per-FTES (2019 dollars)	72	430.38	490.78	-567.99	2520.40
District Indicators					
Median Household Income (2019 dollars)	70	94756.38	38201.66	42377.32	220984.20
2017-18 Minority Share	72	0.51	0.17	0.18	0.93

Matrix of Correlations

Table 6 presents a matrix of correlations for the variables I use in my regression models. I also include a district's rate of Pell and Promise recipients to confirm that this measure is reasonably correlated with median household income[55]. A high correlation in absolute value indicates that my measure of student income, which does not use student-level data, is associated with a more standard measure of student financial need.

[55] I measure a district's rate of Pell and Promise students as the sum of its counts for each grant divided by its total FTES in 2017-18. Since the numerator and denominator are measured in different units, this measure does not carry a logical interpretation but suffices for this exercise.

Table 1.6. Matrix of Correlations

Variable	(1)	(2)	(3)	(4)	(5)
(1) Difference in TCR-per-FTES (2019 dollars)	1.00				
(2) 2017-18 FTES	-0.22	1.00			
(3) 2017-18 Minority Share	0.15	0.03	1.00		
(4) Median Household Income (2019 dollars)	-0.33	0.04	-0.36	1.00	
(5) 2017-18 Rate of Pell and Promise Receipt (Grants per FTES)	0.52	-0.19	0.48	-0.64	1.00

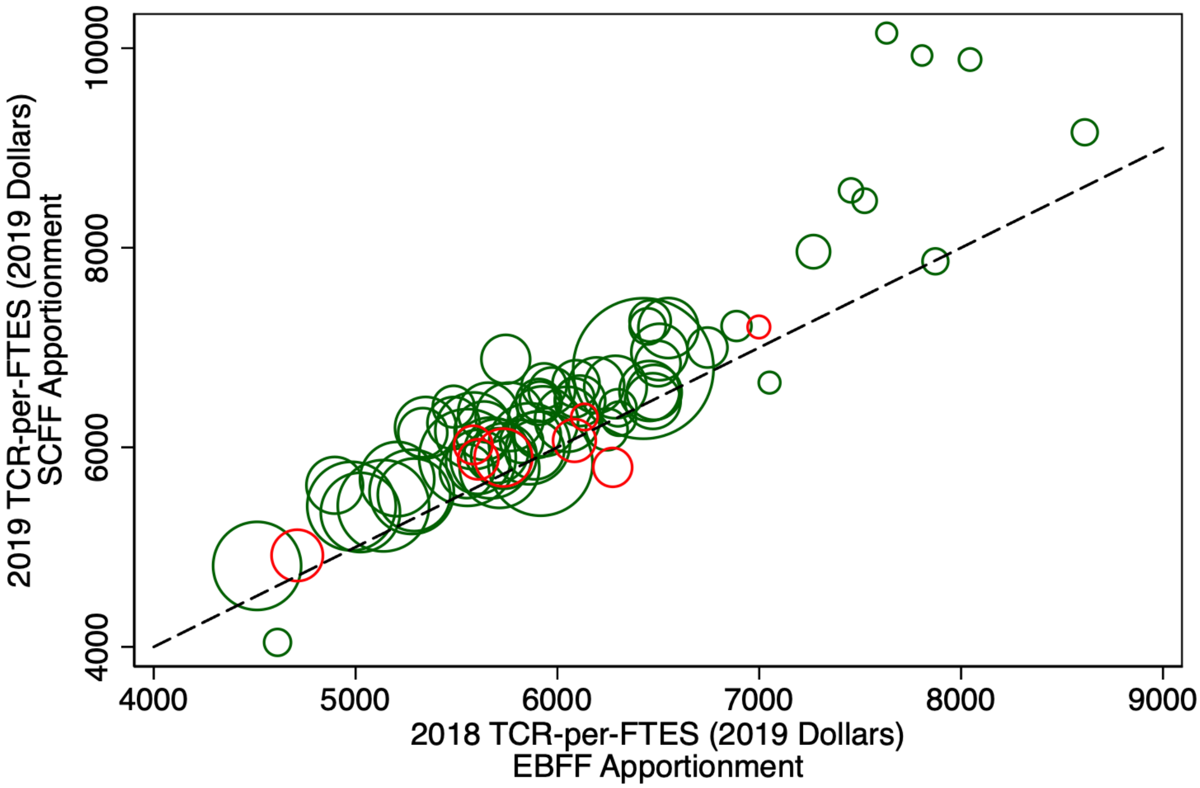
A district's change in TCR-per-FTES associated with the SCFF is negatively correlated with its FTES (-0.22) and with median household income (-0.33), suggesting that low-enrollment and low-income districts are the primary beneficiaries of the SCFF. TCR-per-FTES is positively correlated with minority share, albeit at a lower rate (0.15). Median household income is moderately, negatively correlated with minority share (-0.35) and strongly, negatively correlated with the rate of Pell and Promise receipt (-0.64). This latter correlation indicates that the median household income measure ought to provide a strong representation of student financial need.

Variability in SCFF Apportionment Effects

Figure 7 illustrates the variability in apportionment changes across districts in constant 2019 dollars. Districts with apportionment gains (or losses) are depicted by markers above (or below) the imposed 45-degree line. Each marker size is proportional to a district's 2017-18 FTES. Most districts received a TCR-per-FTES in the SCFF that was slightly higher than the amount they received in the EBFF. This is because the SCFF's hold harmless provision ensures that no district loses apportionment revenue from the formula change. Further, the slight decline in average FTES in 2018-19 relative to 2017-18 implies that the typical district ought to have received a small gain in TCR-per-FTES.

However, several districts received sizeable per-student funding increases from the SCFF. For 10 districts, these gains represent roughly 15 percent or more of their 2017-18 TCR-per-FTES. These winning districts mainly consist of those that received a high TCR-per-FTES in the EBFF and those with low FTES. Finally, notice that a few districts experienced small decreases in TCR-per-FTES. This is possible because the hold harmless funding floor is calculated using a district's 2017-18 FTES. Thus, districts that experience an increase in FTES in the SCFF year may exhibit a decrease in TCR-per-FTES.

Figure 1.6. SCFF Apportionment Gains across CCC Districts



Notes: Each marker represents a CCC district. Red markers denote districts that achieved basic aid status in either funding year. The size of each district marker is proportional to its FTES in 2017-18. This sample includes all 72 districts in the primary analytical sample. The dashed line plots equal 2018 and 2019 TCR-per-FTES. Data are obtained from CCCCO's Apportionment Recalculation 2017-18 and 2018-19.

Table 7 further explains this variability in apportionment across years using ordinary least squares (OLS) modeling. I model a district's change in TCR-per-FTES in the first SCFF year relative to final EBFF year as a function of its 2017-18 FTES, 2017-18 minority share, and median household income. Models 1 and 2 use the full sample of districts[56] and control for either FTES and minority share or full controls. Model 3 runs the same fully-controlled regression as Model 2 on a sample of only non-Community-Supported districts as a robustness check. For this model and appendix models, I report

[56] Recall that two districts drop from Model 2 because I cannot match them with a median household income value.

a coefficient as "significant" in text if it is statistically significant at the five percent significance level[57]. However, each table reports significance at the one, five, and ten percent levels.

Table 1.7. OLS Results for SCFF Apportionment Changes

Variable	FTES and Minority Share Controls (1)	FTES, Minority Share, and Income Controls (2)	FTES, Minority Share, and Income Controls (3)
2017-18 FTES (Thousands)	-7.44*	-6.93*	-7.44*
	(4.18)	(3.77)	(4.03)
2017-18 Minority Share	460.35*	159.5	70.67
	(262.91)	(358.08)	(382.62)
Median Household Income		-3.92**	-3.42*
(Thousands of 2019 dollars)		(1.76)	(1.92)
Constant	318.51	837.23**	864.12**
	(214.14)	(401.63)	(425.21)
R^2	0.07	0.15	0.12
Sample (Observations)	All Districts (72)	All Districts (70)	Non-Community-Supported Districts (62)

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.10

In Model 1, I find that neither a district's FTES nor its minority share is significantly associated with its change in TCR. The first coefficient implies that a 1,000 FTES increase is associated with an average TCR decrease of $7.44 per FTES across years. Since the minority share variable is measured as a fraction, its coefficient implies

[57] In a larger sample of districts, I would choose a lower significance level. This is because the SCFF's funding changes are "mechanical" and thus I expect the relationship between TCR changes and district indicators to be precisely estimated. However, given the small sample size (a high of 72 districts and a low of 61 districts across models), a five percent significance level seems appropriate for this exercise.

that a one percentage point increase in minority share is associated with an average TCR increase of $4.60 per FTES across years. Model 2 adds the median household income term. I report a negative, significant coefficient for this term which suggests that for each $1,000 decrease in median household income, a district's TCR increases by an average $3.92 per FTES across years. Inclusion of this term nets a significant portion of variation from the minority share term. This indicates that the positive relationship between district funding and minority share is largely mediated by student income. In Model 3, I find that the Model 2 coefficients are highly robust to the exclusion of Community-Supported districts. It is most important here that the negative income coefficient, the primary finding in the preceding models, changes little in magnitude. While this coefficient does lose significance, this is not terribly concerning considering the sample decreases in size to only 62 districts.

These results suggest that among the factors of enrollment, race, and income, only income predicts a district's change in TCR-per-FTES associated with the SCFF at a statistically significant level. This finding is sensible because the SCFF directly incentivizes a district's counts of financial aid recipients and undocumented students which are highly correlated to student income. On the other hand, it is less obvious how the formula may differentially affect district apportionment by total enrollment or racial composition.

To further test the robustness of Table 7 Model 2 results, I run four additional models which are displayed in Appendix Table D1. Models 1 and 2 explore how the exclusion of Los Angeles Community College District, which introduces a rightward skew in FTES, affects model results. I modify Table 7 Model 2 by either replacing the linear FTES term with FTES transformed by a natural log or by removing Los Angeles from the sample. The median household income coefficient is -3.09 and -3.74 in these robustness checks, respectively. In either case, this coefficient only decreases slightly relative to the coefficient of -3.92 reported in Table 7 Model 2 and does not lose significance. I conclude that the negative relationship between district funding and student income is robust to the exclusion of Los Angeles district.

Model 3 replaces the median household income term with a district's rate of Pell and Promise recipients relative to its FTES. I use this robustness check to confirm that when controlling for this measure which is directly incentivized by the SCFF, the relationship between district funding and student income strengthens. I find that the coefficient for Pell and Promise receipt is indeed positive[58] and significant. While the interpretation of this coefficient is neither intuitive[59] nor directly comparable to that of median household income, I compare this model's r-squared to that of Table 7 Model 2 to infer whether this variable is more predictive of the change in TCR-per-FTES. The R-squared increases from 0.15 in Table 7 Model 2 to 0.29 in Table D1 Model 3. I conclude that the rate of Pell and Promise recipients adds explanatory power to the model which confirms this logic check.

Finally, Table D1 Model 4 runs Table 7 Model 2 using a weighted least squares (WLS) regression with weights determined by a district's 2017-18 FTES. By assigning larger weights to larger districts, this model estimates the SCFF-associated funding change to the average student whereas the main model estimates this change to the average district. This model reports a median household income coefficient of -0.93 which is much smaller than the main model coefficient and not statistically significant. This implies that the relationship between district funding changes and student income

[58] The sign of this coefficient logically flips relative to that of median household income. A higher rate of grant receipt indicates a higher level of student need whereas a higher median household income indicates a lower level of student need.
[59] Recall that the measure uses summed grants in the numerator and FTES in the denominator.

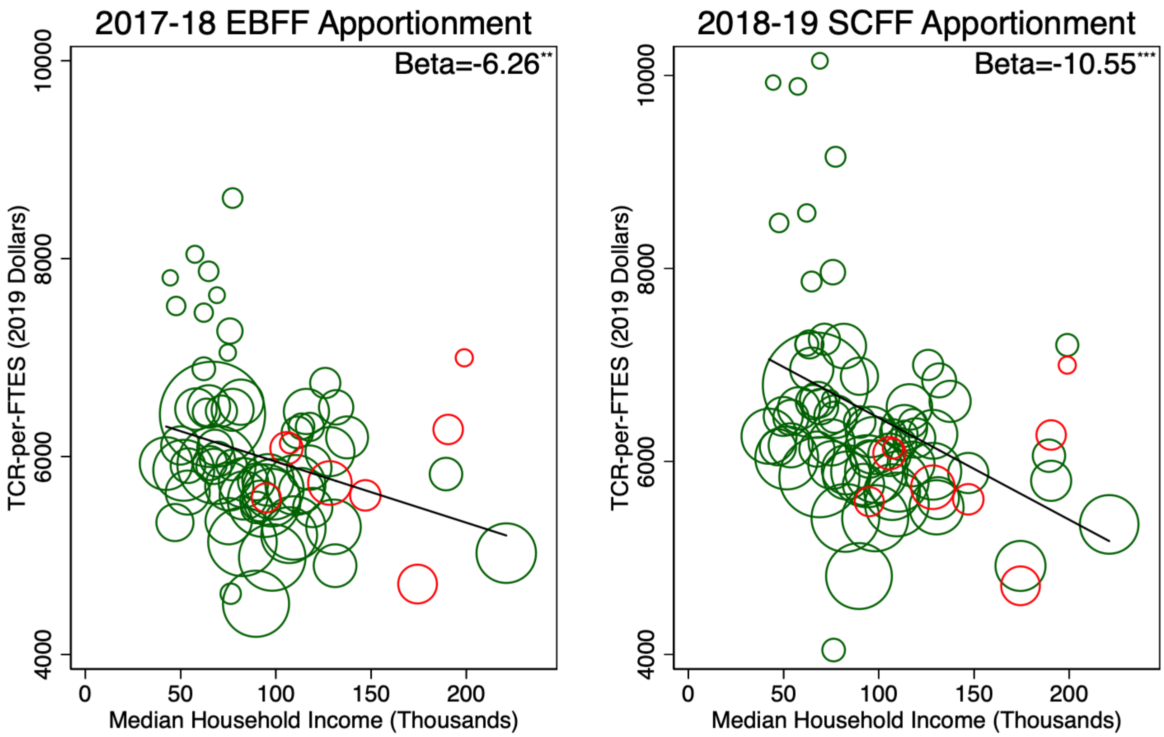
reported in the main model is driven by smaller districts. This is confirmed by Figure 7 which shows several small districts well above the 45-degree line. In turn, the main model overstates the funding increase experienced by the average lower-income student since many of them attend larger schools.

Still, I interpret WLS results with some caution. WLS regression produces biased estimates of population averaged effects when there is unmodeled heterogeneity in treatment effects. (Solon et al., 2013). Since the present model is intended to illustrate the average funding changes associated with a simple set of district characteristics, there are certainly factors that affect funding changes which are omitted from this model (e.g., district degree counts incentivized by the SCFF).

Relationship between District Funding and Student Income across Formulas

Figure 8 further illustrates how the relationship between district funding and student income changed across the EBFF and SCFF. Each marker size is proportional to each district's FTES in the corresponding funding year. Fitted lines display the bivariate relationship between TCR-per-FTES and median household income in each formula. Listed beta coefficients report these slopes, each which is statistically significant. In the EBFF, each $1,000 decrease in median household income, a district's TCR increases by $6.26 per FTES. In the SCFF, the same income change is associated with an $10.55 increase in TCR-per-FTES, a nearly 70 percent increase in absolute value. In Appendix Figure D1, I display the regression results from Figure 8 using WLS with weights determined by a district's FTES. I again observe that the SCFF strengthened the relationship between TCR-per-FTES and median household income, albeit by a smaller margin.

Figure 1.7. Relationship between TCR-per-FTES and Student Income in the EBFF and SCFF



Notes: Each marker represents a CCC district. Red markers denote districts that achieved Community-Supported status in either year. The size of each marker is proportional to a district's FTES in a given year. Sample includes 70 districts that have a non-missing median household income. Fitted lines and reported beta coefficients represent the linear relationship between TCR-per-FTES in a given funding year and median household income.
***p<0.01, **p<0.05

It may be surprising that the EBFF's apportionment was even moderately progressive considering this formula funded districts at equalized rates. I find that this effect is driven by the EBFF's basic allocation rather than instructional revenue. That is, when I regress each of these funding components in per-FTES terms onto a district's FTES, minority share, and median household income, the income coefficient is only negative and significant in the basic allocation model. I present these results in Table D2. A plausible explanation for this is that the basic allocation includes the Rural Access Grant which likely benefits lower-income districts disproportionately.

Finally, I determine whether the increase in funding progressivity seen in Figure 8 is statistically significant. I regress a district's TCR-per-FTES onto an SCFF indicator, median household income, and the interaction between these two variables. The SCFF indicator equals one for district observations in the 2018-19 funding year and zero otherwise. The interaction coefficient represents the SCFF's effect on the relationship between district funding and student income.

Table D3 displays this regression result in Model 1 along with robustness checks in Models 2-4. In Model 1, I find that the interaction coefficient is not statistically significant. In Models 2, I replace the median household income with a district's rate of Pell and Promise receipt in both the main and interaction effect. In Model 3, I add FTES and minority share controls. In Model 4, I run Model 1 using WLS with weights determined by a district's 2017-18 FTES. The interaction coefficient is not significant in any of these models.

Since it is clear that relationship between funding and financial aid receipt is mechanically stronger in the SCFF, these checks suggest that the lack of statistical significance in Model 1 does not indicate a small SCFF effect on funding progressivity. Rather, the lack of statistical significance across models is likely driven by a small sample and omitted variables that determine a district's SCFF-associated funding changes such as the degree counts.

Conclusion

In this report, I illustrate the importance of district apportionment in CCC finance. Apportionment funding makes up a majority of a typical district's discretionary revenue and is thus crucial to the CCC system's educational operations.

Further, the state's funding formula, which determines a district's apportionment funds, significantly impacts the adequacy and equity in CCC funding.

My primary contribution is describing the funding changes associated with the state's adoption of the SCFF in 2018-19 in both qualitative and quantitative terms. I explain that the SCFF replaced a substantial portion of instructional revenue, which was invariant across districts in per-FTES terms, with the supplemental and student success allocations. These new allocations compensated districts for their levels of financial aid recipients, undocumented students, and eight student success outcomes. One may expect that the monetization of financial aid receipt and undocumented students increased progressivity in CCC funding. However, because the SCFF also included performance-based workload measures and a hold harmless provision that protected districts against apportionment losses from the formula change, the manner in which the SCFF distributed apportionment gains across districts is ambiguous.

In my empirical analysis, I model a district's change in TCR-per-FTES between the final EBFF funding year and initial SCFF funding year in constant dollars. I find that the SCFF increased district TCR-per-FTES by an average 7 percent. However, this rate varied significantly as some districts experienced substantial apportionment gains and others experienced small losses. As expected, districts serving lower-income students benefitted disproportionately from the SCFF. For each $1,000 decrease in median household income, a district's TCR increased by an average $4 per FTES. While the EBFF also apportioned revenue progressively, the linear relationship between a district's median household income and its TCR-per-FTES was strengthened by the SCFF. This coefficient increased in absolute value from -6.45 to -10.77, a roughly 70 percent increase. Thus, the SCFF increased progressivity in district apportionment.

In future work, I will consider whether the SCFF was effective in fulfilling the state's broader call for CCC reform. For instance, the state incorporated performance-based workload measures in the formula to increase the rate of degree completion and reduce the time to degree among CCC students. I will analyze whether the SCFF's financial incentives were effective in modifying district behavior to improve performance in these areas. These results will contribute to the existing literature on performance-based incentives in public education and whether states should consider using these reforms as a means of bolstering achievement among community college students.

Glossary

Apportionment revenue—Revenue that is allocated to districts according to the state's funding formula.

Base FTES—A district's prior year funded FTES.

Base revenue—A district's current year apportionment computed under a funding formula using prior year FTES levels and current year funding rates.

Basic allocation—A district's basic allocation is a lump sum apportionment that is a function of its number of colleges and education centers and prior year FTES.

California Community Colleges Chancellor's Office (CCCCO)—The office responsible for allocating state revenue across community college districts.

California Promise Grant—A state grant which covers enrollment fees for low-income students.

Career Development and College Preparation (CDCP)— This program provides additional funding to noncredit courses that emphasize vocational and precollegiate training through noncredit certificate programs.

Categorical programs—District educational programs that often focus on student support services (e.g. Veterans Education). Categorical revenues are restricted for expenditure on their corresponding programs. Restrictions are set by either the state or federal government.

Community-Supported—This status denotes a district that generates a large amount local property tax revenue and thus does not receive State General Fund Apportionment revenue.

Credit courses—These courses align with a district's recommended curriculum for an associate degree. They must be graded and meet a requisite level of academic intensity.

District apportionment—The state's process for allocating funds across districts according to a funding formula.

Education Protection Account—This district fund was created in 2012 by Proposition 30 to supplement district apportionment revenue with new tax revenue generated by its enacting legislation. Its revenue differs from State General Fund Apportionment revenue in that it is not subject to Legislative cuts and is apportioned to all districts regardless of Community-Supported status.

Full-Time Equivalent Students (FTES)—This measures student enrollment by the number of provided hours of student instruction. One FTES is equivalent to 525 instruction hours, the estimated instructional hours for a typical full-time student.

General Fund—A General Fund is a primary operating fund used by a government entity. Both CCC districts and the state use a General Fund for discretionary spending.

Instructional revenue—Revenue apportioned to districts on the basis of credit, noncredit, and CDCP FTES.

Minimum guarantee—The K-14 education funding level set by the California Legislature under the Prop 98 framework.

Noncredit courses—These courses are free to students and do not count towards associate degree completion. They often support students who are non-native English speakers, precollegiate learners, preparing for citizenship, preparing to enter the workforce, and seeking to improve life skills.

Pell Grant—A federal grant which covers tuition for a student who demonstrates a requisite level of financial need on their Free Application for Federal Student Aid.

Proposition 13—An amendment passed in 1978 that reduced California's property taxes and removed most taxing authority from local district governing boards.

Proposition 98—An amendment passed in 1998 that establishes a framework for the Legislature's funding of K-14 education.

Restricted revenue—District revenue with externally-set restrictions on expenditure.

State General Fund Apportionment—The state uses this fund to fulfill non-Community-Supported districts' TCR using revenue from its General Fund.

Student enrollment fees—CCC resident student tuition.

Student success allocation—An SCFF funding component which allocates revenue according to a district's number of student success outcomes including associate degrees and credit certificates.

Supplemental allocation—An SCFF funding component which allocates revenue according to a district's number of Pell Grant recipients, Promise grant recipients, and undocumented students.

Total Computational Revenue (TCR)—A district's formula-computed entitlement, measured annually by the CCCCO.

Unrestricted revenue—District revenue that may be spent in a mostly discretionary manner.

Workload-based entitlement—A district's apportionment revenue received for its recorded workload measures as computed by a funding formula.

Workload measure—A measure established by a funding formula which quantifies district services.

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Appendix A: District Budgeting

The CCC Budget and Accounting Manual states that districts use fund accounting to segregate their financial information according to varying spending objectives and restrictions. A district fund is a "fiscal and accounting entity with a self-balancing set of accounts recording cash and other financial resources, together with all related liabilities and residual equity or fund balances and changes therein." I illustrate an organizational map of district funds along with their revenue compositions in Figure A1. At the broadest level, each fund can be categorized into three groups: Governmental, Proprietary, and Fiduciary Funds. This grouping is based in accounting principles which vary by revenue type but are consistent within each group. In 2018-19, district Governmental Funds represented 84 percent of total CCC revenue, while Fiduciary and Proprietary Funds made up 14 percent and 3 percent, respectively.

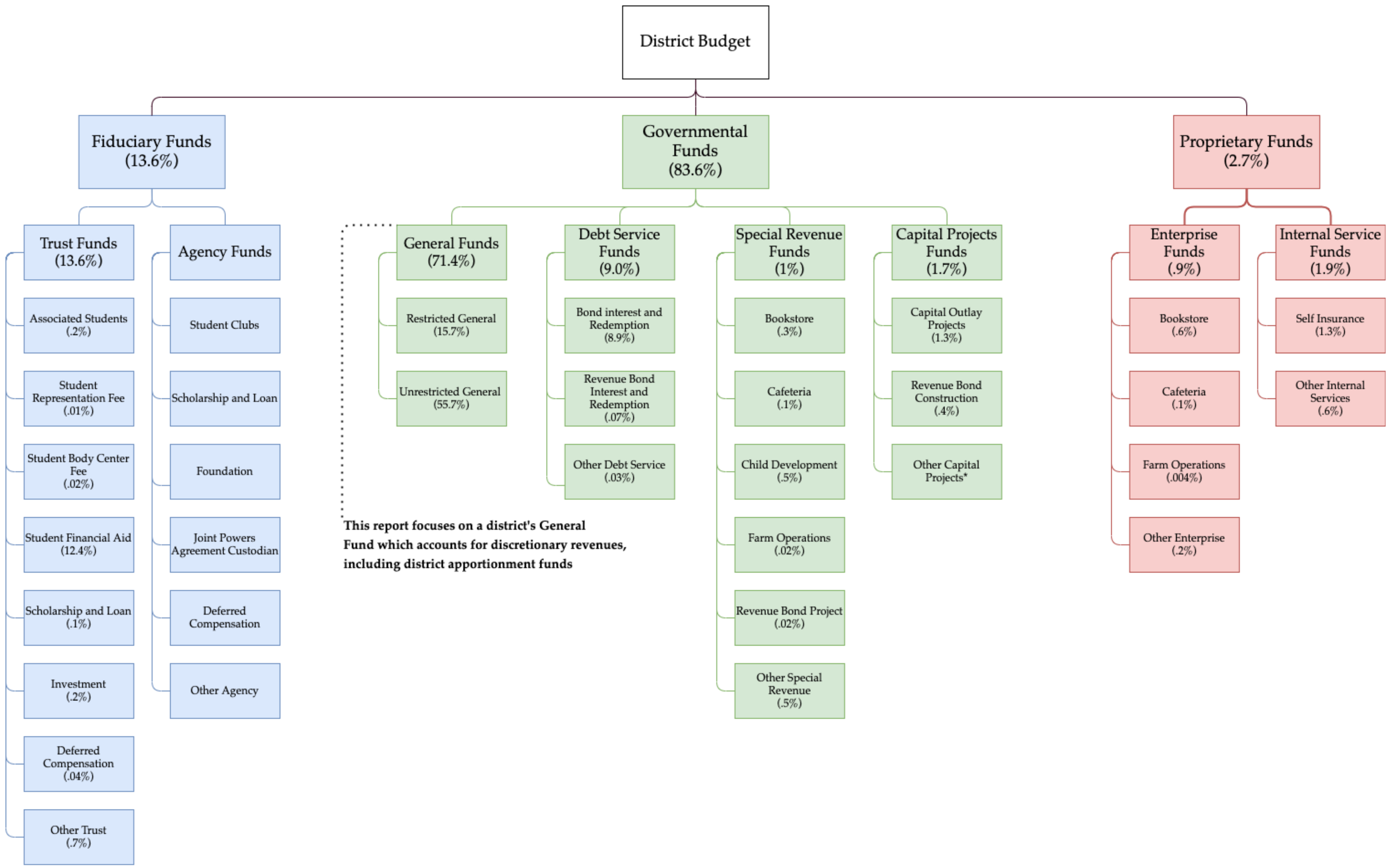
Governmental Funds as used to account for "operations associated with [a district's] educational objectives (CCCCO, 2012). Governmental sub-funds include Restricted and Unrestricted General Funds, Debt Service Funds, Special Revenue Funds, and Capital Projects Funds. I cover General Funds in detail in Sections II.A and II.B. Debt Service Funds account for long-term debt and interest and include revenues from special property tax levies. Special Revenue Funds are used to "account for the proceeds of specific revenue sources whose expenditures are legally restricted". These include the Bookstore Fund, Cafeteria Fund, and Child Development Fund (i.e. district proceeds from child care). Capital Projects Funds account for the "acquisition or construction of major capital facilities and other capital outlay projects (other than those financed by Proprietary and Fiduciary Funds)."

Proprietary Funds are used to account for "ongoing activities that, because of their income-producing character, are similar to those found in the private sector"

(CCCCO, 2012). Proprietary sub-funds include Enterprise and Internal Service Funds. Enterprise are used for an operation "when it is the intent of the governing board to operate as a business and to account for its total operating costs." For instance, if a district's governing board intends to recover the costs of providing a bookstore or cafeteria service, it will account for these proceeds in Enterprise sub-funds or else will use Special Revenue sub-funds. Internal Service Funds account for the "financing of goods and services provided by one department or organizational unit to other units on a cost-reimbursement". These include a Self-Insurance sub-fund which accounts for Worker's Compensation and Health Insurance programs.

Finally, Fiduciary Funds are used to account for "assets held by [a] district in a trustee or agency capacity for individuals, private organizations, other governmental units, and/or other funds." Fiduciary sub-funds include Trust Funds, over which a district has some spending discretion, and Agency Funds, over which a district has little to no spending discretion. These funds account for financial aid, scholarships and loans, and student fees for a student body center and clubs.

Figure 1.A1. Aggregate CCC Revenue across District Funds



Notes: Reported percentages are computed from the CCCCO's CCFS-311 Reports. Each percentage computes the total CCC revenue in the corresponding fund divided by the total CCC revenue across all funds in the 2018-19 fiscal year. Data for total revenue and fund revenue for each fund with a reported percentage (except the Restricted/Unrestricted General Fund) is obtained from *Summary of Financial Transactions by Fund*. Data for Unrestricted General Fund revenue is obtained from *Summary of Unrestricted General Fund Transactions*. Restricted General Fund revenue is imputed as the difference between the total District General Funds revenue and the Unrestricted General Fund revenue. There are no reported percentages for Agency Funds or its sub-funds. Since districts may not spend these funds, they do not report them as revenue. The organization of funds is obtained from *CCC Budget and Accounting Manual*. Sub-funds are listed exhaustively for the General Fund only because other funds are not covered in detail by this report.

Appendix B: The Program-Based Funding Formula

The PBFF was a notoriously convoluted funding formula (Murphy, 2004). It established six categories of district operations, or programs, eligible for funding including credit and noncredit instruction. These categories were quantified by varying workload measures (e.g. FTES for instruction). It set standard funding rates for each measure according to the cost of meeting measurable benchmarks (e.g. maintaining a set student-faculty ratio). The PBFF determined a district's apportionment as the sum of its reported workload measures multiplied by their corresponding rates. This sum was adjusted for factors including for inflation, district growth, and district scale. However, this computation was severely complicated by the use of "percentage of standard" rates which scaled down a district's standard funding rate. This step affected districts unequally and was in fact designed to maintain district funding disparities that existed upon implementation of the PBFF (Jaschik, 2006; Murphy, 2004; T. M. Scott, 2016).

The funding outcomes of the PBFF were far from optimal. First, there were large disparities in funding per FTES across districts. About a quarter of districts' revenue fell outside 90-110 percent of the state-average per-FTES funding (Jaschik, 2006). Further, it was ineffective at allocating additional revenue for districts experiencing rapid enrollment growth. Finally, it strongly disincentivized noncredit instruction by funding it at less than a third of the rate of credit instruction (Murphy, 2004).

Appendix C: Growth, Stability, and Restoration Funding

In this appendix section, I describe mechanisms contained in both the EBFF and SCFF that manage a district's incentives for FTES growth and mitigate revenue losses associated with FTES declines. These provisions work very similarly across the formulas. However, the SCFF's implementation made one key change which I note in the final subsection.

Growth Funding

Growth funds set incentives for districts to grow their enrollment to a level that the state is willing to fund (Murphy, 2004). First, the state annually budgets a fixed amount of Prop 98 growth funds for the CCC system[60] (Petek, 2020). Next, the CCCCO allocates these funds across districts by assigning each district a growth rate (Growth and Decline, 2007). It multiplies this growth rate[61] by a district's base FTES for credit, noncredit, and CDCP to determine the caps of funded FTES a district may gain in a given year. Each FTES cap is multiplied by the current marginal rates to form a district's growth revenue caps.

Thus, while a district may increase its FTES levels by any amount, its revenue gain for each FTES type is capped. Any increase in a district's FTES in excess of its cap represents unfunded FTES[62]. While a district is guaranteed the potential for growth revenue (i.e. the CCCCO assigns a minimum growth rate), its realized growth

[60] The size of growth funds depends on changes in the adult population, unemployment, and the State's budget condition (Petek, 2020; Taylor, 2015).
[61] In practice, a district's growth rate for credit, noncredit, and CDCP FTES need not be equal. However, I simplify this section by assuming a constant growth rate across instructional categories.
[62] The CCCCO may use one district's unachieved growth revenue to fund another district's unfunded FTES (Murphy, 2004).

ultimately depends on its prior year actual FTES. Thus, if the district cannot grow its enrollment, it does receive growth funds.

A district can optimally manage its FTES by increasing it up to but not exceeding its growth caps each year (Murphy, 2004). Any excess will result in the same amount of apportioned revenue which the district must then allocate across more students. Further, because the growth cap is computed using base FTES, unfunded FTES will not benefit a district's revenue in the subsequent year either[63].

The CCCCO's growth rate formula allocates growth potential unequally across districts and has varied over the EBFF's operational period. Over the first few years, the CCCCO retained its growth formula from the PBFF which focused primarily on a district's[64] "demand indicators" such as the size of its adult population and high school graduates (Growth and Decline, 2007; Murphy, 2004). This was later revised in 2009-10 to include factors for a district's unemployment rate and amount of unfunded FTES. In 2015-16, the formula was revised again to focus more on a district's "need indicators" such as educational attainment and literacy rates (Mullen & Justice, 2018).

Stability and Restoration

The EBFF adopted two new mechanisms, "stability" and "restoration", to improve a district's fiscal stability during an FTES decline, an instance in which its actual FTES is less than base FTES[65] (Growth and Decline, 2007). Stability delays a district's instructional revenue loss associated with a decline by one year (Barton et al.,

[63] That is, a district maximizes its base FTES in the subsequent year by achieving its growth cap in the current year. Unfunded FTES do not increase future base FTES.
[64] Indicators across growth formulas use a district's primary county population as a sample to measure the relevant factors (Growth and Decline, 2007).
[65] This total loss may be distributed in any manner across credit, noncredit, and CDCP FTES so long as it results in decreased total instructional revenue (Dowd, 2016; Growth and Decline, 2007).

2019; Budget Stability, 2007; Dowd, 2016). In the year of the decline, a district receives stability revenue by the amount of this instructional revenue loss. This allows a district to devise an enrollment strategy and attempt to increase its enrollment back to or above its pre-decline level (Barton et al., 2019). Unless a district succeeds in doing this, it suffers the revenue loss in the year following the decline. Recall from Figure 7 above that a district's FTES decline may result in a basic allocation revenue loss. Stability also provides that a district will experience this loss in the third year following the decline according to its current year FTES if it cannot increase its FTES back to or above its pre-decline level.

Restoration provides a three-year period following a decline[66] during which a district can increase its FTES back to or above its pre-decline level (Barton et al., 2019; Decline Restoration, 2007; Dowd, 2016). A district that does so receives restoration revenue in the year it restores its FTES. This revenue represents a district's cumulative reduction in FTES between the decline year and restoration year funded at the current, marginal FTES rates and adjusted for COLA [67]. If a district cannot restore its FTES in the restoration period, its FTES is re-benched to a lower level of enrollment[68] (Barton et al., 2019). Similar to stability, a district may use restoration consecutively.

[66] The CCCCO does not allocate growth revenue for districts in this restoration period (Growth and Decline, 2007)

[67] A district receives restoration revenue on top of its other apportionment revenues as described above (Gerhard, 2018).

[68] This implies that a district's future use of restoration will offer lower revenue growth potential if it is unable to restore its FTES.

SCFF Changes

Under the SCFF, a district may no longer use the one-year stability provision for credit FTES since the three-year rolling credit FTES measure mitigates the instability caused by an enrollment decline (CCCCO, 2019a). However, it may still use this provision to protect its noncredit and CDCP FTES from decline for one year and its basic allocation for three years.

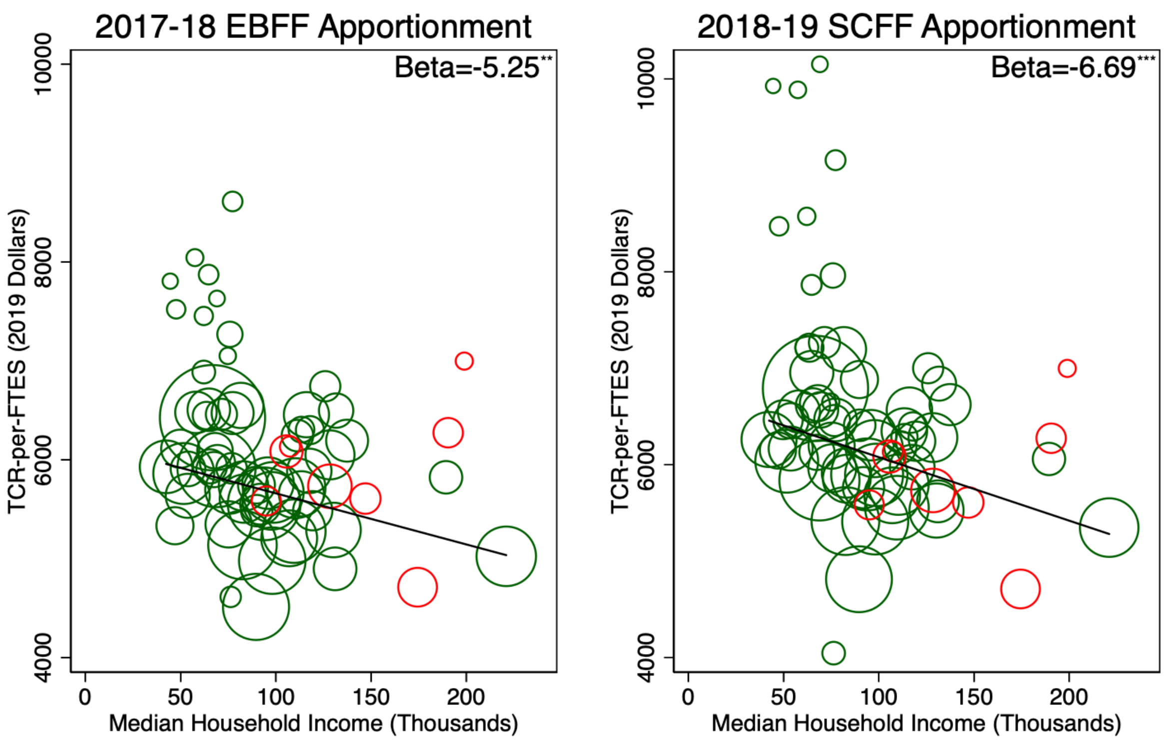
Appendix D: Regression Results

Table 1.D1. OLS Robustness Results for SCFF Apportionment Changes

Variable	Logged FTES (1)	Exclude Los Angeles District (2)	Pell and Promise Indicator (3)	Weighted Results by FTES (4)
2017-18 Logged FTES	-180.20*			
	(95.41)			
2017-18 FTES (Thousands)		-10.24*	-3.75	-2.48*
		(5.23)	(2.98)	(1.40)
2017-18 Minority Share	261.67	129.07	-302.28	453.3
	(312.69)	(368.03)	(382.95)	(275.15)
Median Household Income (Thousands of 2019 dollars)	-3.09** (1.39)	-3.74** (1.68)		-0.93 (1.15)
2017-18 Rate of Pell and Promise Receipt (Grants per FTES)			718.63*** (218.73)	
Constant	2,279.98**	881.82**	-288.62	267.22
	(1108.83)	(419.94)	(197.98)	(231.72)
R^2	0.21	0.17	0.29	0.12
Observations	70	68	72	70

Notes: Each regression model presented in this figure serves as a robustness check for the fully-controlled Model 3 in Table 7. Models 1 and 2 test its robustness to skewed FTES data by either logging FTES or removing Los Angeles Community College District from the sample. Model 3 tests its robustness to the measurement of student income by replacing median household income with a district's rate of Pell and Promise recipients. Model 4 uses Weighted Least Squares Regression with weights determined by district 2017-18 FTES. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.10

Figure 1.D1. Relationship between TCR-per-FTES and Student Income in the EBFF and SCFF: Weighted Least Squares Results using FTES Weights



Notes: Each marker represents a CCC district. Red markers denote districts that achieved Community-Supported status in either year. The size of each marker is proportional to a district's FTES in a given year. Sample includes 70 districts that have a non-missing median household income. Fitted lines and reported beta coefficients represent the linear relationship between TCR-per-FTES in a given funding year and median household income.
***p<0.01, **p<0.05

Table 1.D2. OLS Results for per-FTES Basic Allocation or Instructional Revenue in the EBFF

Variable	2017-18 per-FTES Basic Allocation (1)	2017-18 Instructional Revenue (2)
2017-18 FTES (Thousands)	-19.62***	-1.25
	(7.00)	(6.37)
2017-18 Minority Share	-1153.14***	417.45
	(339.71)	(402.01)
Median Household Income	-6.62***	0.95
(Thousands of 2019 dollars)	(1.81)	(1.86)
Constant	2,289.53***	4,483.86***
	(395.93)	(365.49)
R^2	0.43	0.02
Observations	70	70

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.10

Table 1.D3. Change in Funding Progressivity Associated with the SCFF

Variable	Median Household Income (1)	Pell and Promise Robustness Check (2)	Promise Robustness Check with Full Controls (3)	Household Income: WLS with FTES Weights (4)
Median Household Income (Thousands of 2019 dollars)	-6.17**			-5.17***
	(2.64)			(1.71)
SCFF Indicator	940.14*	-380.38	-380.38	572.11**
	(480.14)	(539.30)	(478.19)	(287.70)
Median Household Income (Thousands of 2019 dollars) X SCFF Indicator	-4.38			-1.53
	(4.26)			(2.39)
2017-18 Rate of Pell and Promise Receipt (Grants per FTES)		937.57***	1,136.83***	
		(252.06)	(242.23)	
2017-18 Rate of Pell and Promise Receipt (Grants per FTES) X SCFF Indicator		694.43	694.43*	
		(430.56)	(380.68)	
2017-18 FTES (Thousands)			-0.02**	
			(0.01)	
2017-18 Minority Share			-1,348.48***	
			(412.67)	
Constant	-6,565.32***	4,764.04***	5,463.73***	6,177.13***
	(281.20)	(327.50)	(369.38)	(198.12)
R^2	0.18	0.32	0.44	0.21
Number of Districts	70	72	72	70
Observations	140	144	144	140

Notes: Each model uses district TCR-per-FTES as the outcome. Model 4 uses Weighted Least Squares Regression with weights determined by district 2017-18 FTES Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.10

Paper 2: Impact of Financial Aid Incentives on Student Receipt in the California Community College System

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Abstract

Financial aid programs are essential for the accessibility of higher education in the United States. California has attempted to expand access to the California Community College (CCC) system among financial aid recipients with its recent adoption of the Student-Centered Funding Formula (SCFF). This formula pays CCC districts for their counts of students who receive a Pell Grant or state fee-waiver, known as the Promise Grant. In this paper, I assess the SCFF's effects Pell and Promise Grant receipt in the CCC system. I draw on student-level administrative data from the CCC system in the 2015-2019 period. I use an interrupted time series model to estimate systemwide effects and comparative interrupted time series models to estimate differential effects across college groups. Results show that the SCFF was associated with an increase Pell Grant receipt but not Promise Grant receipt systemwide. Heterogeneity in awarding across colleges was not driven by the extent to which a college was affected by financial aid incentives. However, for Pell awarding, colleges that could award grants to a larger number of eligible non-recipients made larger awarding gains.

Introduction

Financial aid is crucial to the accessibility of postsecondary education in the United States. Access to financial aid may increase a student's postsecondary enrollment, educational attainment, and labor market success (Denning et al., 2019; Dunlop, 2013; Page & Scott-Clayton, 2016; Wiederspan, 2016). However, the complexity of the financial aid system imposes significant barriers to eligible students, thereby limiting student receipt and program efficacy (Bettinger et al., 2012; Dynarski & Wiederspan, 2012; Scott-Clayton, 2015). In particular, the burdensome application process of the Pell Grant Program restricts aid take-up among eligible students (Bettinger et al., 2012; Dynarski & Wiederspan, 2012; Scott-Clayton, 2015).

Recent research documents the extent to which financial aid administration hinders student receipt in the California Community Colleges (CCC) system, the largest postsecondary education system in the nation. Only about 80 percent of eligible CCC student applicants receive a Pell Grant (Martorell & Friedmann, 2018). This rate varies considerably across colleges and appears driven by campus-level financial aid administration (Friedmann & Martorell, 2019). This suggests that college policies and advising services may be one important way to increase uptake among students.

The recently-adopted Student-Centered Funding Formula (SCFF) may serve as a catalyst for reform in aid administration across the CCC system. This formula increases incentives for aid take-up among college administrators by paying districts for their counts of students who receive a Pell Grant or state-funded fee waiver, known as the Promise Grant.

In this paper, I examine whether the SCFF increased student receipt of Pell and Promise Grants in the CCC system. For Pell receipt, I explore the extent to which awarding changes are driven by three mechanisms: FAFSA submission, Pell receipt conditional on FAFSA submission, and Pell receipt conditional on Pell eligibility. This illustrates whether colleges boosted awarding through increased student application, improved aid administration among filers, and/or improved aid administration among eligible students.

I use several analytical strategies to measure the SCFF's effects on awarding. I use an interrupted time series (ITS) model to estimate systemwide policy effects. I find that the SCFF increased the likelihood that a student receives a Pell Grant but not a Promise Grant. This effect was driven by an increase in FAFSA submission and Pell receipt conditional on eligibility.

I also use comparative interrupted time series (CITS) models with two distinct grouping methods to compare effects across CCC colleges that ought to have been disproportionately affected by the SCFF. The first method leverages the fact that while most districts depend on revenue from the SCFF's aid incentives, a few districts are funded through local taxes and thus do not receive additional revenue from the SCFF's incentives. I find the unexpected result that awarding gains among financially unaffected colleges were equal to or larger than awarding gains among financially affected colleges. The second method leverages the variability in a college's baseline Pell take-up rate among eligible students. I find that low-take-up colleges made larger Pell awarding gains, driven by an increase in Pell receipt conditional on Pell eligibility and, to a lesser extent, Pell receipt conditional on FAFSA submission. This indicates that low-take-up colleges responded to the SCFF primarily by improving aid administration among eligible students.

Background

Prior Literature

Financial aid programs are instrumental in providing access to postsecondary education among students with financial barriers (Bailey & Dynarski, 2011; Page & Scott-Clayton, 2016). Rapidly rising tuition costs and stagnant median family income in recent decades have increased the proportion of students that depend on aid to afford college (Federal Reserve Bank of St. Louis, n.d.; National Center for Education Statistics, 2021; Page & Scott-Clayton, 2016). In 2019-20, undergraduate student aid totaled $184 billion. The average undergraduate student received almost $15,000 in aid in the form of grants, loans, tax credits, and work-study (CollegeBoard, 2020).

Prior research finds only moderate evidence that aid programs positively affect student success. For instance, consider recent evidence on the federal Pell Grant Program. While Denning, Turner, and Marx (2019) find large, statistically significant increases in college graduation and earnings associated with student access to Pell Grants, other studies find smaller or null effects (Carruthers & Welch, 2019; Marx & Turner, 2018). In the community college setting, students may benefit from access to the federal, low-interest Stafford Loan through increased course completion (Wiederspan, 2016), associate degree completion (Wiederspan, 2016), and transfer to a four-year institution (Dunlop, 2013; Wiederspan, 2016).

Prior research also highlights that complexity in the financial aid system limits student aid receipt and may dampen the effects of aid on student success (Dynarski & Wiederspan, 2012; Scott-Clayton, 2015). Because families, high schools, and colleges often lack the resources to help students navigate the financial aid system, many students are unaware of their eligibility and unable to take full advantage of their benefits. Notably, the Free Application for Federal Student Aid (FAFSA) process for determining a student's Pell Grant eligibility has received considerable attention (Bettinger et al., 2012; Dynarski & Wiederspan, 2012; Scott-Clayton, 2015). This form is longer than the income tax form used by most households and inhibits application among eligible students, particularly those who are low-income and first-generation college students (Bettinger et al., 2012; Scott-Clayton, 2015).

These challenges imply that a postsecondary institution may play a substantial role in helping students navigate the financial aid system. Martorell and Friedmann (2018) examine Pell take-up across CCC colleges prior to the SCFF's adoption. They find that less than 80 percent of Pell-eligible students[69] receive a Pell Grant. This take-up rate varies considerably across colleges with a range of 60 to 90 percent. Friedmann and Martorell (2019) find that take-up is partly related to college practices, such as requirements for FAFSA verification. This process requires many students who have already submitted a FAFSA to submit additional paperwork to verify FAFSA information. Since a college has discretion in how strongly it pursues verification, this administrative practice may impose additional barriers to student receipt and drive differences in take-up across CCC colleges.

Finally, there is a large body of literature on the effects of performance-based funding in higher education. While these results are not directly comparable to the present paper because of the SCFF's unique focus on aid receipt, they are nonetheless useful in framing how a college may optimally respond to performance incentives. In the community college context, performance incentives often fail to increase the student outcomes that policymakers intend (Hillman et al., 2015; J. Ortagus et al., 2020;

[69] That is, students who appear to meet all eligibility requirements including FAFSA submission.

Tandberg et al., 2014), especially if they represent a small proportion of an institution's revenue (Li & Kennedy, 2018). Further, colleges may respond to performance incentives by targeting shorter-run student outcomes at the expense of longer-run student outcomes since these may be affected in a relatively quick and inexpensive manner (Dougherty & Reddy, 2011; Hillman et al., 2015, 2018; J. Ortagus et al., 2020).

These findings help frame how a college may optimally respond to financial aid incentives in the present policy context. Broadly speaking, a college may reform its aid practices, policies, and services by increasing aid application among students who did not previously apply and/or to increasing receipt among students who previously applied and demonstrated eligibility but did not receive benefits. For the Pell Grant, a college may identify the latter mechanism as a more efficient means of increasing receipt. The application mechanism may involve considerable expenditure because of the lengthy FAFSA application process. For instance, it may involve hiring additional financial aid counselors to assist students in navigating the application and verification processes. It may also be ineffective if the affected students are not eligible for Pell. On the other hand, increasing receipt among eligible students may require lower additional costs and offer higher gains in receipt, particularly for a college that has a large number of Pell-eligible students who have not previously accessed benefits. For instance, a college may simply adopt email or text reminders to notify eligible students of their eligibility and what steps they must take to receive benefits.

California Community Colleges and the Student-Centered Funding Formula

The CCC system is a massive network of public community colleges which serves more than two million students annually (California Department of Finance, 2021). It consists of 73 districts which may contain one or multiple of the CCC's 116 colleges. The state is primarily responsible for funding the CCC system (Smith, 2018). It uses a centralized funding formula to apportion state revenue across CCC districts.

In 2018-19, the state shifted its funding priorities for the CCC system by replacing an enrollment-based funding formula with the SCFF. The prior formula apportioned revenue on a per-student basis and weighted all students equally (Smith, 2018). The SCFF weights funding differently to fund low-income students more highly. It does so by paying a district a set rate for its counts of enrolled students who receive a Pell Grant and state fee-waiver, known as the Promise Grant. On average, revenue from these incentives represent roughly 20 percent of a district's apportionment revenue. Note that the SCFF also adopted incentives for student success outcomes which serve as the focus of *Paper 3: Impact of Degree Incentives on Degree Production in the California Community College System.* For more detailed coverage on the SCFF's incentives and the mechanical differences between it and the prior formula, see *Paper 1: District Apportionment in the California Community College System.*

The state's adoption of the SCFF ostensibly changed the financial incentives of CCC districts. Under the prior enrollment-based formula, a district maximized its apportionment by increasing total student enrollment. Under the SCFF, a district faces reduced incentives to increase total enrollment and new incentives to increase enrollment of financial aid recipients specifically. Crucially, the SCFF's enacting legislation contained a hold harmless provision which protected district apportionment against losses in the first two policy years[70]. Thus, while a district faced the risk of

[70] This hold harmless period was ultimately extended several times in subsequent legislation. However, in the first SCFF year, districts operated under the assumption of a two-year window. This hold harmless period perfectly overlaps with the two SCFF years included in the present analysis. I discuss how this provision may affect model results below.

revenue declines resulting from low awarding beginning in the SCFF's third operational year, it may have responded to aid incentives with less urgency because of this provision.

Some CCC districts known as "Community-Supported" (CS) districts do not receive apportionment revenue from the state's funding formula (Smith, 2018). This is because CS districts raise a higher amount of apportionment revenue through local taxation than what the state would otherwise provide through the funding formula. These districts retain local apportionment revenue but do not receive additional apportionment revenue from the state. While all districts, including CS districts, received the signal that the state was placing increased emphasis on serving lower-income students, CS districts ought to have had no change in financial incentives from the SCFF. I use CS status as one grouping method in my analytical models since colleges in non-CS districts[71] are financially affected by aid incentives whereas colleges in CS districts are financially unaffected. I discuss the difference in incentives between CS and non-CS colleges in more detail below.

A college has two primary mechanisms with which it can increase aid receipt. It may increase application among students who have previously not used aid and/or increase receipt among students who have previously applied for aid but did not receive it. The prior findings that a college may respond to performance incentives by targeting student outcomes that it can efficiently impact (Dougherty & Reddy, 2011; Hillman et al., 2015, 2018; J. Ortagus et al., 2020) and that many eligible CCC students do not receive Pell Grants (Martorell & Friedmann, 2018) suggest that colleges

[71] CS is technically a district-level status since the state apportions revenue at this level. However, for the remainder of the paper, I use this status to denote a district in the context of the state's apportionment process or a district's colleges in the context of grouping in my analytical models.

responded by targeting the latter mechanism. In particular, I posit that colleges with low Pell take-up among eligible students prior to the SCFF would be especially likely to exert efforts to increase receipt among this group. This type of reform may offer these colleges "low-hanging fruit" to increase revenue from aid incentives. I use a college's baseline Pell take-up rate as a second grouping method in my analytical models to explore whether low-take-up colleges made larger awarding gains than high-take-up colleges using this mechanism.

Pell Grants

The federal Pell Grant Program promotes access to postsecondary education through need-based grants (CollegeBoard, 2020). Pell Grants are the largest source of federal aid offered to undergraduates in the United States (Federal Student Aid, 2021). In 2018-19, more than a third of all undergraduate students in the nation received a Pell Grant which averaged $4,418. In the same year, roughly 18 percent of CCC students received a Pell Grant which averaged $3,696[72].

Pell Grant eligibility and benefits are determined by a student's cost of attendance, expected family contribution (EFC), and enrollment status (e.g., part-time or full time) (Congressional Research Service, 2018). EFC is computed using information collected by the FAFSA including a student's individual and family income and assets. Each year, there is a maximum EFC above which a student is not financially eligible for a Pell Grant. An eligible student must also enroll in at least six units, hold a high school diploma (or equivalent credential), not hold a bachelor's degree, and be a U.S. citizen.

[72] I use CCCCO administrative data files to compute these and all subsequent statistics in this section.

Further, to receive a Pell Grant over multiple terms, a student must maintain Satisfactory Academic Progress (SAP), described in-text below and in Appendix A.

Student application for a Pell Grant is nuanced process (Dynarski & Wiederspan, 2012; Martorell & Friedmann, 2018; Scott-Clayton, 2015). Students must submit personal and family financial records through the FAFSA. Next, receiving colleges may ask students to verify their FAFSA information with additional paperwork (Martorell & Friedmann, 2018). This may involve submitting tax documents to prove that the income listed on the FAFSA is correct.

Promise Grants

The California College Promise Grant[73] is a state-funded program that reduces financial barriers to the CCC system by waiving student tuition (CCCCO, 2019). In 2018-19, over 40 percent of CCC students received a Promise Grant which averaged $700[74]. To be eligible for a Promise Grant, a student must be a California resident, enroll in credit courses[75], and demonstrate financial need (CCCCO, 2019). Like Pell recipients, students who receive a Promise Grant in multiple terms must meet SAP, albeit under a different set of requirements. These are discussed in-text below and in Appendix A.

The Promise Grant application process is simpler than that of the Pell Grant (Martorell & Friedmann, 2018). While a student may submit their FAFSA to apply, they may also submit a simpler "short form" which does not require verification (CCCCO,

[73] The Promise Grant was formerly known as the Board of Governors Fee Waiver.
[74] For reference, the annual cost of full-time attendance was $1,104 in this year.
[75] Non-credit courses are free in the CCC system. Thus, students enrolled in exclusively non-credit courses would owe zero tuition.

2019d; Martorell & Friedmann, 2018). Students may demonstrate financial need through one of the five following methods:

1. They or their family receives benefits from CalWORKS (California's implementation of Temporary Assistance to Needy Families), Supplemental Security Income, or General Assistance.
2. They or their family meets the state's low-income criteria[76].
3. They submit a FAFSA with an eligible EFC[77].
4. They meet special student classifications (e.g., homeless youth, dependents of veterans).
5. They qualify for a non-resident tuition exemption, a program which typically serves undocumented students (CCCCO, 2019d).

In the SCFF's first operational year, the state expanded Promise Grant eligibility (WestEd, 2018). This allowed first-time, full-time students who do not have financial need to receive a Promise Grant. However, the SCFF does not pay a district for its Promise recipients who qualify through this expansion. Thus, I do not code these students as Promise Grant recipients in my analysis. This also ensures that I am able to separate the SCFF's effect on Promise receipt from this eligibility expansion.

Students may receive Pell and Promise Grants concurrently. In 2018-19, more than 97 percent of CCC Pell recipients also received a Promise Grant. As Martorell and Friedman (2018) note, since a Promise recipient does not owe tuition, the receipt of both benefits implies that a student may use their Pell Grant to pay for other expenses such as textbooks and rent.

[76] In 2018-19, the income threshold for a student who is a dependent in a four-member household was set at $36,900.
[77] A student is eligible if their level of demonstrated need on the FAFSA is at least $1,104, the annual cost of full-time attendance.

Research Questions

In the present study, I assess whether the SCFF's incentives increased student receipt of financial aid. My research questions are grounded in the prior findings that colleges tend to target low-cost reforms in response to performance incentives (Dougherty & Reddy, 2011; Hillman et al., 2015, 2018; J. Ortagus et al., 2020) and that college Pell take-up rates were relatively low and variable in the CCC system prior the SCFF (Martorell & Friedmann, 2018). This implies that colleges with lower take-up rates have a ready way to improve Pell receipt rates. These questions are:

1. Does the rate of Pell and Promise Grant receipt increase systemwide following the adoption of the SCFF?
2. How does the effect in RQ1 vary across colleges?
   A. Do colleges that are financially affected by aid incentives exhibit larger gains in awarding than those that are financially unaffected?
   B. Do colleges with lower baseline Pell take-up exhibit larger gains in awarding?
3. To what extent is the in change in Pell receipt in RQ1 and RQ2 driven by an increase in FAFSA submission, Pell receipt conditional on FAFSA submission, and/or Pell receipt conditional on Pell eligibility?

Data and Methods

Data Construction

I use administrative files from the CCCCO to construct a dataset that tracks term-level student receipt of Pell and Promise Grants. These files contain rich student-level data for each student who attends the CCC. I merge files that track annual FAFSA information (e.g., EFC) and term-level financial aid awards (e.g., Pell and Promise Grant receipt), course information (e.g., units enrolled, units completed, GPA), and student characteristics (e.g., race, gender, age).

There are two key analytical variables that are not recorded by the CCCCO. The first is a college's CS status. I use this variable in my first college grouping method that compares awarding effects across colleges that are financially affected or unaffected by aid incentives. I use CCCCO apportionment data to flag a district's colleges as CS in a given year if its local tax revenues exceed the revenue that the state would have otherwise provided through the funding formula. The second is the maximum EFC that is eligible for a Pell Grant in a given year. I use this variable in my second college grouping method that compares awarding effects across colleges with high and low baseline Pell take-up. By restricting to students with eligible EFCs, I estimate take-up among students who are eligible for a Pell Grant. I code this variable using publicly available Pell Grant schedules.

I use an analytical period of the 2015-16 through 2019-20 academic years. This captures three years prior to and two years following the SCFF's implementation in fall 2018. I choose this period so that there are a sufficient number of pre-intervention data points to meet the requirements of a CITS model (Somers et al., 2013). However, I choose not to include additional years prior to 2015-16 since Pell and Promise grant receipt rose sharply in those years before flattening out during my analytical period. Including those prior years may therefore bias my analytical models (see Appendix Figure B1).

Sampled terms include each fall and spring term in the analytical period. I exclude all summer terms because aid receipt and enrollment patterns are not directly comparable to that of fall and spring. Additionally, I exclude winter quarters for the three CCC campuses that use a quarter system. Notably, the spring 2020 term marked the onset of the Covid-19 pandemic. However, because financial aid and enrollment decisions were made in January whereas school shutdowns began in March, I expect that the pandemic did not affect the outcomes I explore in this study. I find that declines in enrollment and aid receipt between fall 2019 and spring 2020 were somewhat larger than fall-to-spring declines in previous academic years[78]. I discuss the implications of including this term below.

Analytical Samples

I make a series of restrictions to create two analytical samples that capture students who meet various non-financial criteria for the Pell and Promise Grant, respectively, in each sampled term. Note that I can only observe financial information through the FAFSA among student filers. Because increased application is one mechanism through which the SCFF may have increased aid receipt, I do not restrict on FAFSA application or financial information. However, by dropping students who are ineligible for aid because of other factors, described below for each award type, I try to net out changes in the composition of eligible students over time. This ought to improve identification of the SCFF's effects in my analytical models.

Pell Sample

Pell eligibility depends upon on a student's prior educational attainment, number of credits enrolled, and academic progress (Congressional Research Service,

[78] I examine these changes using my Pell sample, described below. In spring 2020, the counts of enrolled students, Pell recipients, and Promise recipients declined by 10.8 percent, 15.6 percent, and 14.5 percent, respectively, relative to fall 2019. In the prior three academic years, these fall-to-spring declines take a range of 7.7 percent to 9.4 percent, 11.4 percent to 12.2 percent, and 8.9 percent to 10.8 percent.

2018). I remove students who are not eligible based on these criteria. First, I drop students who do not hold a high school diploma or equivalent (including students dually enrolled in high school and CCC courses) and students who hold a Bachelor's degree. Second, I drop students who are not enrolled in courses[79]. Third, for students who fail to make Pell SAP requirements in at least two total terms, I drop them in all terms following the second failing term. I flag a student as failing to make SAP in single term if either their cumulative GPA falls below a 2.0, cumulative percent units completed falls below 67 percent, or cumulative units attempted towards their degree exceeds 90. I use a student's entire CCC transcript including years prior to the analytical period to generate these cumulative variables. For a discussion of college SAP policies across the CCC system and my choice of coding practice, see Appendix A.

Finally, I drop students who attend colleges that do not offer credit instruction or that do not administer Pell Grants in the analytical period. I observe three colleges that offer credit instruction but record zero FAFSA submissions or Pell recipients in at least one year during the 2015-2019 analytical period[80]. I drop each student-term in which the student attends one of these three colleges during non-awarding year. However, these students may still appear in the sample for terms in which they attended sampled colleges.

[79] These are comprised of students who use college services but do not enroll in courses. Though Pell Grant recipients must enroll in at least six units, I choose a weaker enrollment restriction to construct this sample. I am concerned that sampling students who enroll in six or more units may pose an endogeneity bias in my analytical models since a student's enrollment may depend in part on their application for a Pell Grant.
[80] One such campus opened in 2015 while another offers exclusively online-based instruction.

Promise Sample

Promise eligibility is restricted to CA residents who owe tuition and meet academic requirements. I remove students who are not eligible based on these criteria. First, I drop students who are not California residents. Second, I drop students who do not owe tuition. These include students who are not enrolled in credit courses and those dually enrolled in high school and CCC courses. Third, for students who fail to make Promise SAP requirements in at least two consecutive terms, I drop them from my sample in all terms following the second failing term. I flag a student as failing to make SAP in a given term if their cumulative GPA falls below a 2.0 and/or cumulative percent units completed falls below 50 percent. For a discussion of college SAP policies across the CCC system and my choice of coding practice, see Appendix A.

Finally, I drop students who attend colleges that do not offer credit instruction or that do not administer Promise Grants in the analytical period. There is a single college that offers credit but does not administer the Promise Grant in each analytical term. Table 1 presents the counts of students and colleges in each analytical year for both the Pell and Promise samples.

Table 2.1. Annual Counts of Student and College in the Pell and Promise Sample

	Pell Sample		Promise Sample	
Year	Student Count	College Count	Student Count	College Count
2015	1,480,767	113	1,848,991	114
2016	1,449,600	113	1,828,816	114
2017	1,431,848	114	1,829,843	114
2018	1,403,683	114	1,830,746	114
2019	1,356,463	114	1,791,039	114

Notes: Year denotes the fall of a corresponding academic year.

Summary Statistics

Table 2 presents summary statistics for both Pell and Promise samples in the 2017-18 baseline year which preceded the SCFF's implementation. The samples are comprised of students that highly similar across race and gender. Students in the Pell sample are roughly two years younger than those of the Promise sample, on average. This is because in the Pell sample, I drop students who are fail to make SAP due to a large number of cumulative units and are thus are older, on average. However, I do not restrict on cumulative units in the Promise sample since there is no corresponding SAP criterion for this grant. Students in the Pell sample also enroll in roughly .7 more units, on average. This difference is also a result of the differences in SAP restrictions across samples. In the Pell sample, I select a group of students with stronger academic performance who tend to enroll in more units.

Table 2.2. Summary Statistics for Pell and Promise Samples

Variable	Pell Sample	Promise Sample
Outcomes		
Submitted FAFSA	0.524	--
	(0.499)	
Received Pell Grant	0.313	--
	(0.464)	
Received Pell Conditional on FAFSA Submission	0.588	--
	(0.492)	
Received Pell Conditional on Pell Eligibility	0.738	--
	(0.440)	
Received Promise Grant	--	0.539
		(0.498)
Covariates		
Hispanic	0.467	0.451
	(0.499)	(0.498)
White	0.274	0.289
	(0.446)	(0.453)
Asian	0.097	0.096
	(0.296)	(0.294)
Black	0.056	0.054
	(0.230)	(0.226)
Female	0.517	0.530
	(0.500)	(0.499)
Age	24.281	26.371
	(9.751)	(11.186)
Units Enrolled	8.984	8.280
	(4.783)	(4.802)
Sample Size	862,189	1,105,644
Number of Colleges	114	114

Notes: Standard deviations displayed in parentheses. Each observation represents a unique student observation in the 2017-18 baseline academic year. For duplicated student observations across terms and colleges, a single observation is selected at random.

Methods

I employ a series of models to estimate the SCFF's effect on a student's likelihood of receiving a Pell or Promise Grant. To understand how colleges reformed Pell administration in response to the SCFF, I also estimate the SCFF's effect on the likelihood of FAFSA submission, Pell receipt conditional on FAFSA submission, and Pell receipt conditional on Pell eligibility. If changes in Pell receipt are driven by FAFSA submission, this indicates that colleges responded to the policy by encouraging student application. If changes are driven by receipt conditional on FAFSA submission or receipt conditional on Pell eligibility, this indicates that colleges responded to the policy by improving aid administration among filing or eligible students. For instance, this may involve counseling students who are Pell-eligible to take up aid or reducing administrative barriers to proving aid eligibility (e.g., those related to verification). In additional to the Pell sample restrictions above, I flag a student as Pell-eligible in a given term if they enroll in six or more units in that term and submit a FAFSA with a Pell-eligible EFC. I discuss this coding decision in more detail below.

Unbiased estimates of the SCFF's effects on student financial aid outcomes could most credibly be obtained if a subset of CCC colleges had been randomly assigned to "treatment" by the SCFF while the remaining colleges had remained funded by the prior enrollment-based formula. Then, I could estimate an effect as the difference in outcome across treatment and control groups. Of course, these conditions were not present in the SCFF's implementation and thus, this ideal research design is unavailable for use.

Alternatively, an available but naïve design is an Ordinary Least Squares (OLS) model that compares changes in a college outcome pre- and post-SCFF. Consider the following model

$$(1)\ Y_{ist} = \beta_1 SCFF_t + \beta_2 \alpha_s + e_{ist}$$

where Y_{ist} represents Pell or Promise receipt for student i in college s in term t, $SCFF_t$ is a binary indicator which equals 1 if the SCFF was operational in term t and 0 otherwise, and α_s represents college fixed effects which capture time-invariant heterogeneities across colleges. The SCFF's effect is captured by $\hat{\beta}_1$. However, this OLS estimator may be biased if it captures trends in aid receipt that are contemporaneous but unrelated to the policy.

Interrupted Time Series

To improve upon identification, I use an ITS design to estimate the effects of the SCFF on systemwide financial aid receipt. This model takes the following form

$$(2)\ Y_{ist} = \beta_1 Term_t + \beta_2 SCFF_t + \beta_3 Terms\_Since\_SCFF_t + \beta_4 Fall_t + \beta_5 X_{ist} + \beta_6 \alpha_s + e_{ist}$$

where $Term_t$ equals the number of terms passed since the start of the observational period. There are 10 total terms where the first term denotes fall 2015 and the final term denotes spring 2020. $Terms\_Since\_SCFF_t$ equals the number of terms passed since the SCFF's implementation in fall 2018. This equals one through four in the sixth through tenth term in which the SCFF was operational and zero otherwise. $Fall_t$ is an indicator that equals one in fall terms and zero in spring terms. X_{ist} is a vector of time-varying student characteristics. In each analytical model described in this section, I include controls for student race, gender, age, and number of enrolled units in a given term. Each other variable is defined as before.

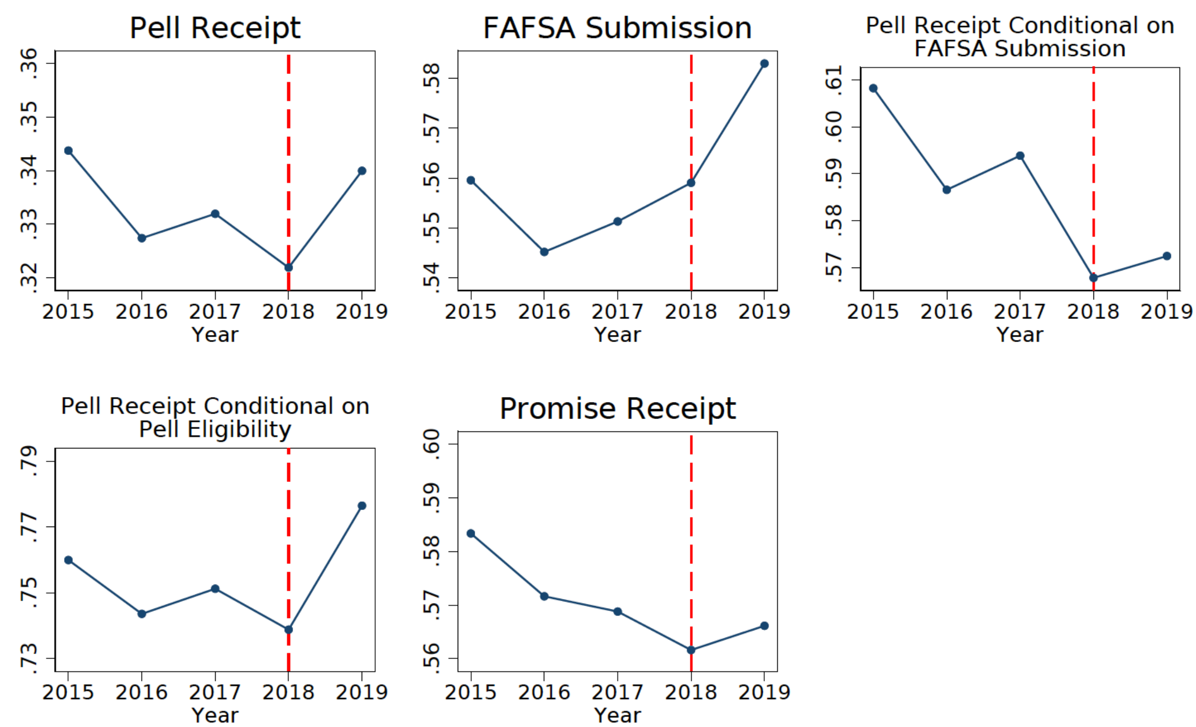
$\hat{\beta}_1$ nets out time-varying differences in an outcome that are measured in the pre-SCFF period. $\hat{\beta}_2$ and $\hat{\beta}_3$ and capture the SCFF's effect on an outcome in a level shift and slope change, respectively. I measure the SCFF's effect by spring 2020, the fourth and final operational term in the analytical period, as $\hat{\beta}_2 + 4 \cdot \hat{\beta}_3$. By controlling for variation related to seasons (i.e., fall or spring term), student characteristics, and college characteristics, I attempt to isolate changes in aid receipt associated with the SCFF. In this model and the CITS and event-study models discussed below, I use standard errors clustered at the college level to account for non-independence between college-years[81]. ITS results are displayed in Table 4 below.

ITS results are valid if the pre-SCFF trend estimated by $\hat{\beta}_1$ would have continued in the post-SCFF period had the policy not been implemented. While untestable, there is reason to question whether this assumption holds. Figure 1 presents the mean of each awarding outcome across the analytical period. I compute means at the year level to net out variability across terms in the same academic year where aid application and receipt is higher in fall relative to spring. Each awarding outcome exhibits a negative trend prior to the SCFF's adoption. This decline appears to result from a prior awarding spike in the mid-2010s following the Great Recession (see Appendix Figure B1 for a longer time trend). While it is plausible that this pre-SCFF decline would have continued in the absence of intervention, it may have in fact tapered. In this case, $\hat{\beta}_1$ would be downward biased and the estimated policy effect would be upward biased.

[81] In each model, I experiment with clustering standard errors at the year and college-year level to account for potential serial correlation and underreporting of standard errors (Cameron & Miller, 2015). However, I find that clustering by college results in the largest standard errors. I choose this method so that estimates of model precision are conservative.

For this reason, ITS results should be interpreted with caution. Below, I try to strengthen the identification of policy effects by introducing comparison college groups.

Figure 2.1. Mean Model Outcomes in 2015-2019



Notes: Each point displays a mean outcome across all sampled CCC colleges in a given year. Years denote the fall of a corresponding academic year. Pell receipt (conditional or unconditional) and FAFSA submission rates are computed using the Pell sample whereas the Promise rate is computed using the Promise sample. A student is Pell-eligible if they submit a FAFSA with a Pell-eligible EFC and enroll in 6+ units in a given term. The vertical line denotes the first operational SCFF year.

Comparative Interrupted Time Series

I also use a CITS framework to estimate the SCFF's effects on Pell and Promise receipt across different margins. As before, I model the three Pell mechanisms of FAFSA submission, Pell receipt conditional on FAFSA submission, and Pell receipt conditional on Pell eligibility. By comparing effects across college groups that ought to have been more or less affected by the policy, I attempt to "difference out" time-varying confounds which may bias the ITS. For this reason, I consider the CITS to be a stronger analytical technique, although it cannot estimate total policy effects across the CCC system like the ITS does. I use two distinct college grouping methods, described below, to identify colleges that ought to have been more or less financially affected by the SCFF reforms (to determine the specific effect of financial incentives) and to identify colleges that had different levels of pre-SCFF Pell take-up (to determine the mechanisms through which colleges may have changed aid distribution). I use these groups to estimate the following CITS model

(3) $Y_{ist} = \beta_1 Term_t + \beta_2 SCFF_t + \beta_3 Terms\_Since\_SCFF_t + \beta_4 Term_t \cdot Treat_s + \beta_5 SCFF_t \cdot Treat_s + \beta_6 Terms\_Since\_SCFF_t \cdot Treat_s + \beta_7 Fall_t + \beta_8 X_{ist} + \beta_9 \alpha_s + e_{ist}$

where $Treat_s$ equals 1 if college s is ostensibly more affected by the policy and 0 otherwise. Each other variable is defined as before.

The terms $\hat{\beta}_1$ and $\hat{\beta}_4$ net out time-varying differences in a given outcome that are measured in the pre-SCFF period. These differences are estimated separately for each group. $\hat{\beta}_5$ and $\hat{\beta}_6$ capture the SCFF's marginal level shift and marginal change in slope, respectively, among more affected colleges compared to that of less affected colleges.

Under the CITS model, policy effects change over time if the slope coefficients are non-zero. I measure the effect of the SCFF's incentives on more affected colleges by spring 2020, the fourth and final treated term, as $\hat{\beta}_2 + \hat{\beta}_5 + 4 \cdot (\hat{\beta}_3 + \hat{\beta}_6)$. I measure this same effect on less affected colleges as $\hat{\beta}_2 + 4 \cdot \hat{\beta}_3$. Finally, I measure the "net effect" of SCFF incentives as the effect on more affected colleges less the effect on less affected colleges, or $\hat{\beta}_5 + 4 \cdot \hat{\beta}_6$. I present these results in Table 5 and 6 below.

CITS results are valid if $\hat{\beta}_1$ and $\hat{\beta}_4$ are properly estimated such that there are not remaining time-varying differences across college groups that are related to awarding outcomes (Dee & Jacob, 2011; Hallberg et al., 2018). While this assumption is again untestable, I use two methods to provide suggestive evidence that it is satisfied. First, I show in Figures B1 and B2 that trends in aid outcomes appear highly comparable across each set of college groups over a long time horizon. This supports model validity since each group appears to be exposed to the same set of policies and secular trends. Second, I use event-study models, describe below, to examine how net policy effects change over time prior to the SCFF. I present these results in Figures 3 and 4 below. I find that these pre-policy differences between more- and less-treated groups are statistically insignificant and/or demonstrate a mostly linear trend. This suggests that the linear fit of pre-SCFF trends is properly specified which further supports CITS validity.

Event-Study with Comparison Groups

I supplement this CITS approach with a second set of models that use an event-study framework. These models allow me to compare policy effects across college groups at different time points more flexibly. In turn, I can assess whether groups exhibit insignificant or linear changes prior to the SCFF to show that $\hat{\beta}_1$ and $\hat{\beta}_4$ from Equation (3) are properly estimated. I can also examine how the net effect magnitude changes over the SCFF's duration to assess whether college responses appear immediate or lagged.

I modify Equation (3) to use an event-study model which uses the same two grouping methods, discussed below. This model takes the following form

(4) $Y_{ist=} \sum_{j=1}^{5} \gamma_j (Lead\ j)_t + \sum_{j=1}^{5} \delta_j ((Lead\ j)_t \cdot Treat_s) + \sum_{k=1}^{4} \tau_k (Lag\ k)_t + \sum_{k=1}^{4} \varphi_k ((Lag\ k)_t \cdot Treat_s) + \beta_1 X_{ist} + \beta_2 \alpha_s + e_{ist}$

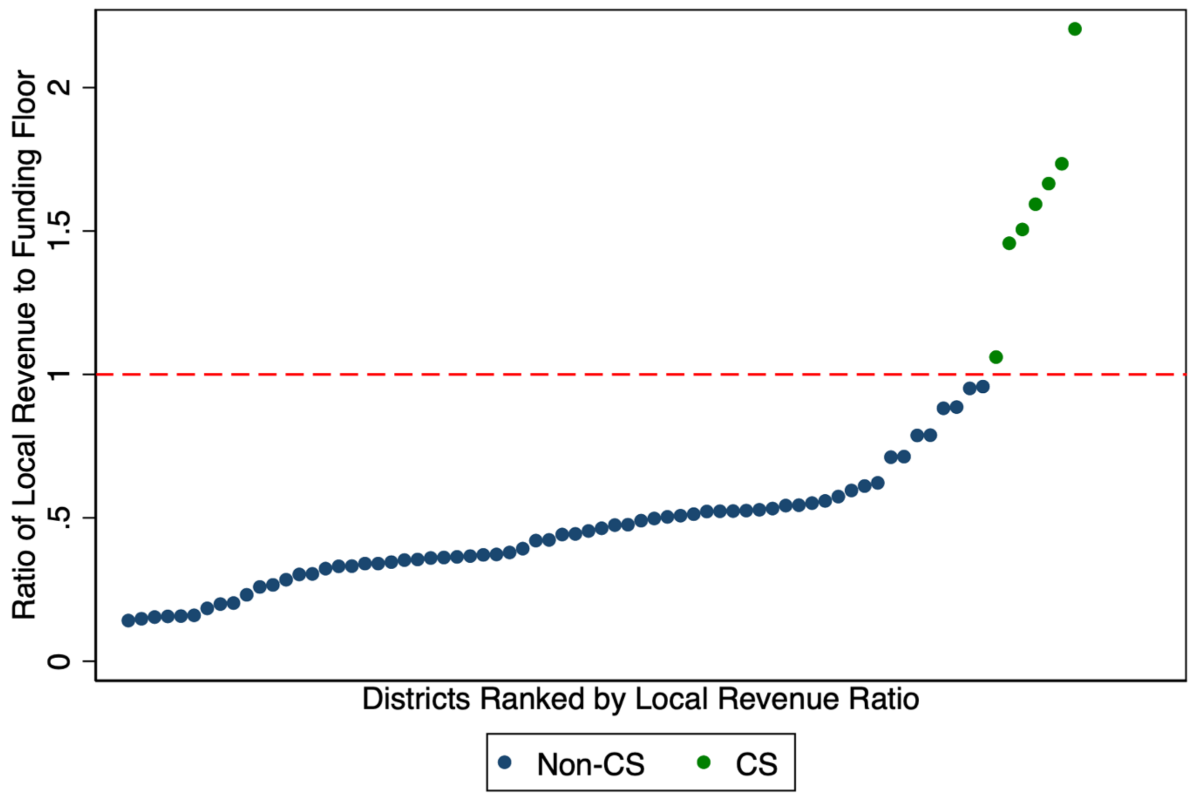
where $(Lead\ j)_t$ is a set of indicators for the five terms which preceded SCFF in the analytical period. I omit the sixth and final lead term from this equation to serve as a baseline period. $(Lag\ k)_t$ is a set of indicators for the four terms in which the SCFF was operational. $\hat{\delta}_j$ captures the difference in college groups in a given lead term less that difference in the baseline sixth term. $\hat{\varphi}_j$ captures this same change for a given lag term. I present results from this specification in Figures 3 and 4 below.

Grouping by Community Supported (CS) Status

In the first grouping method used to estimate Equations (3) and (4), I compare policy effects across groups that are financially affected or unaffected by the SCFF's aid incentives. The first group is non-CS colleges which I denote as financially-affected because they receive apportionment revenue, including aid incentives, from the state. That is, the state distributes additional funds to these districts because they do not raise enough local revenues to meet their entitlement determined by a funding formula in a given year. The second group is CS colleges which I denote as financially-unaffected because they do not receive apportionment revenue from the state. This is because they raise enough local revenue to meet their formula entitlement.

Figure 2 illustrates the difference in the extent to which SCFF incentives should have affected colleges across CS status by displaying each district's ratio of local revenue to its funding floor. A district obtains local revenue through taxation. Its funding floor is determined by the state formula according to measures including enrollment (in both the enrollment-based formula and SCFF) and Pell and Promise receipt (in the SCFF only). Each district's "actual" revenue is equal to the greater of its local revenue and funding floor. By definition, a non-CS district's local revenue is less than its funding floor. This difference is paid out by the state. Conversely, a CS district's local revenue exceeds its funding floor. It retains all local revenue but receive no additional apportionment from the state.

Figure 2.2. Local Revenue Ratios across CS and non-CS Districts



Notes: Each marker represents a single district in the 2017-18 apportionment year. The horizontal line marks the threshold above which a district qualifies for CS status. Data is sourced from the CCCCO's Recalculation Apportionment.

The horizontal line displayed in Figure 2 represents the threshold for CS status. For the typical non-CS district, local revenue is less than half of its funding floor which implies that its actual revenue is dependent on its formula-computed floor. However, for the typical CS district, local revenue is more than one-and-a-half times that of its funding floor which implies that its actual revenue is likely to be unaffected by changes to its floor. For instance, the SCFF awarded $919 for each enrolled Pell recipient in its first operational year (CCCCO, 2020). A non-CS district could thus increase its actual revenue by $919 for awarding an additional Pell Grant. However, a CS district gains no actual revenue by awarding an additional Pell Grant.

The only way in which a CS district may benefit financially from increased aid awarding is by expanding its award counts[82] such that its state-computed funding floor exceeds its local revenue. For a district that has local revenue that is one-and-a-half times greater than its funding floor, this feat is implausible. On average, the SCFF's aid incentives comprise only 20 percent of a district's funding floor which implies that this district must expand its aid awards by three-and-a-half-fold before it can receive the $919 for an additional award.

Thus, I reason that while colleges in non-CS districts were financially affected by the SCFF's aid incentives, colleges in CS districts were not. By comparing group differences in awarding outcomes over time, the CITS and event-study models ought to capture the specific effect of the SCFF's aid incentives net of a policy environment with lower-stakes accountability. For instance, to the extent that colleges were treated by the state's emphasis on support for lower-income students in its 2017 *Vision for Success*, this effect ought to be differenced out in the comparison of CS and non-CS colleges.

I code a college as non-CS if its funding floor exceeded its local tax revenues in the 2017-18 baseline year. Otherwise, I code the college as CS. In Appendix C, I discuss a modified coding practice of CS status which compensates for colleges which may be "partially treated" by incentives. In this Appendix, I also present CITS and event-study results for this alternate grouping which are highly similar to those in main text.

[82] A district may also increase formula revenue through degree awarding which is incentivized by the SCFF, albeit at a lower funding rate (CCCCO, 2020c).

Summary Statistics for Pell and Promise Samples by College CS Status

Table 3 presents summary statistics for students in the Pell and Promise samples across CS and non-CS college groups in the 2017-18 baseline year. In each sample, students in non-CS colleges are more likely to be Black or Hispanic and less likely to be Asian or White relative to students in CS colleges. By including demographic controls and college fixed effects in each analytical model, I attempt to net out variation in aid awarding that is related to differences in racial composition across groups. Non-CS students are also more likely to file a FAFSA and receive a Pell or Promise Grant. This is expected because non-CS colleges are located in state regions with relatively weaker tax bases. Students in these college are thus lower-income, on average, and are more likely to use financial aid programs.

Table 2.3. Summary Statistics for CS-Based Groups in the Pell and Promise Sample

	Pell Sample		Promise Sample	
Variable	Non-CS Colleges	CS Colleges	Non-CS Colleges	CS Colleges
Outcomes				
Submitted FAFSA	0.533	0.416	--	--
	(0.499)	(0.493)		
Received Pell Grant	0.320	0.219	--	--
	(0.466)	(0.414)		
Received Pell Conditional on FAFSA Submission	0.591	0.527	--	--
	(0.492)	(0.499)		
Received Pell Conditional on Pell Eligibility	0.675	0.635	--	--
	(0.469)	(0.482)		
Received Promise Grant	--	--	0.551	0.404
			(0.497)	(0.491)
Covariates				
Hispanic	0.476	0.350	0.462	0.321
	(0.499)	(0.477)	(0.499)	(0.467)
White	0.270	0.325	0.283	0.358
	(0.444)	(0.468)	(0.450)	(0.480)
Asian	0.092	0.157	0.091	0.154
	(0.290)	(0.364)	(0.288)	(0.361)
Black	0.058	0.029	0.056	0.028
	(0.234)	(0.167)	(0.230)	(0.164)
Female	0.516	0.529	0.528	0.555
	(0.500)	(0.499)	(0.499)	(0.497)
Age	24.297	24.066	26.280	27.458
	(9.726)	(10.082)	(11.047)	(12.686)
Units Enrolled	8.973	9.114	8.297	8.072
	(4.788)	(4.710)	(4.810)	(4.698)
Sample Size	802,664	59,525	1,020,226	85,418
Number of Colleges	102	12	102	12

Notes: Standard deviations displayed in parentheses. Each observation represents a unique student observation in the 2017-18 baseline academic year. For duplicated student observations across terms and colleges, a single observation is selected at random.

Grouping by Baseline Take-Up Rate

In the second grouping method used to estimate Equations (3) and (4), I compare policy effects among colleges with higher and lower baseline aid take-up (i.e., the proportion of students prior to the SCFF who are eligible for aid and receive benefits). I posit that a college with lower aid take-up before the adoption of aid incentives ought to have increased awarding of Pell and Promise Grants by a greater margin after adoption. This differential effect ought to be driven primarily by an increase in aid receipt among eligible students since this student group offers the potential for increased awarding gains.

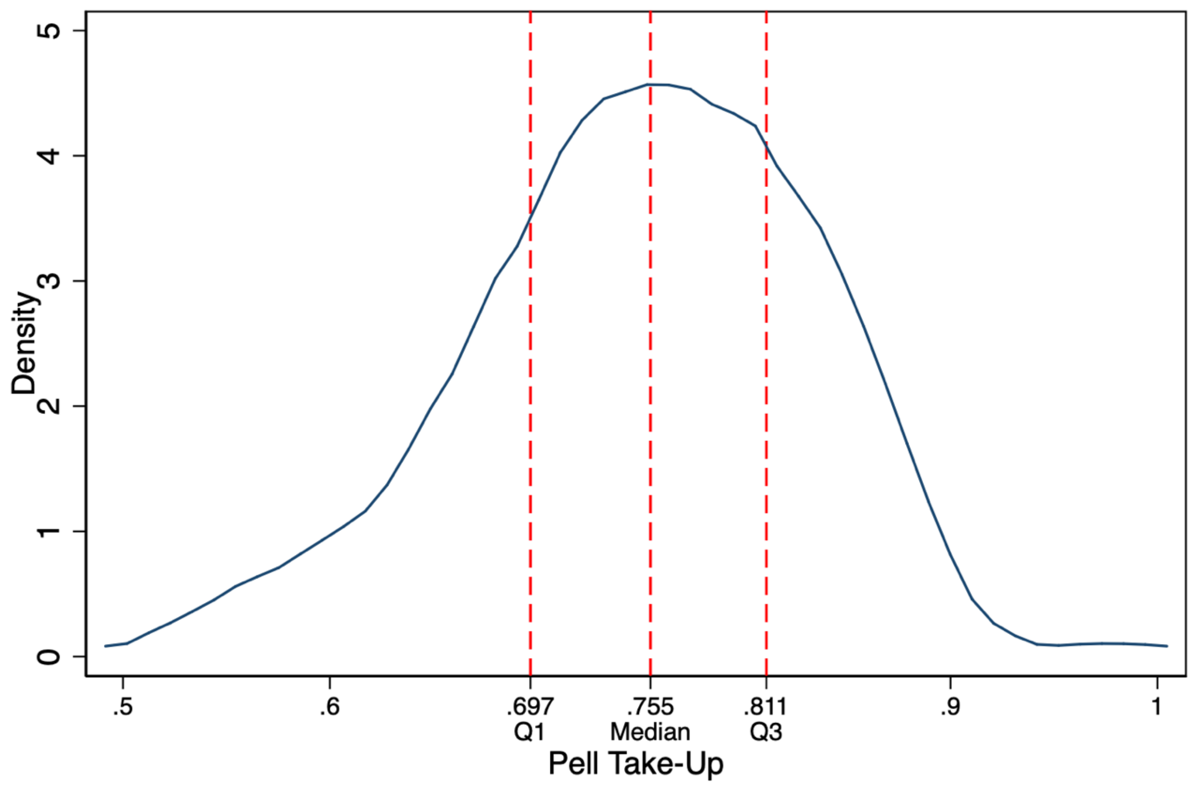
While I am unable to identify students who are eligible for a Promise Grant in the analytical data, I follow Martorell and Friedmann (2018) to identify students who appear to meet all eligibility criteria for a Pell Grant in a given term. Thus, I explore only Pell and FAFSA outcomes in the CITS and event-study models that use this grouping method.

I measure each college's Pell baseline take-up in 2017-18. In addition to the Pell sample restrictions described above, I flag a student as Pell-eligible in a given term if they enroll in at least six units[83] in that term and submit a FAFSA in the corresponding academic year with an EFC that is less than or equal to the maximum EFC in that year. I compute a college's Pell take-up as the proportion of recipients among eligible students where I sum student counts across fall and spring terms. Next, I flag colleges that fall in the top and bottom quartile of this measure which I denote as "high-take-up" and "low--take-up", respectively. Figure 3 displays the distribution of baseline Pell take-up with

[83] Recall that in constructing the Pell sample, I only restrict on student enrollment in a positive number of units. However, I make a stronger restriction for this exercise since I want to drop all students who may not receive a Pell Grant due to enrollment in a number of units less than the six units required to receive a Pell Grant.

thresholds for the high- and low-take-up groups. In the CITS and event-study models, I compare policy effects across these groups and drop colleges that fall in the middle two quartiles. I choose this method so that the high- and low-take-up groups do not consist of colleges with relatively similar baseline take-up.

Figure 2.3. Distribution of Baseline Pell Take-up with Quartiles



Notes: Figure displays the distribution of Pell take-up in the 2017-18 baseline year for 114 sampled colleges. In my CITS and event-study model, I flag colleges that have lower take-up than the first quartile (Q1) threshold as low-take-up. I flag colleges that have higher take-up than the third quartile (Q3) threshold as high-take-up.

Summary Statistics for Take-Up-Based Groups in the Pell Sample

Table 4 presents summary statistics across high- and low-take-up colleges in the Pell sample. Students in low-take-up colleges are more likely to be Asian or Black but less likely to be Hispanic or White relative to students in high-take-up colleges. Average enrollment is almost one unit lower among students in low-take-up colleges. Again, I include model covariates for demographics and enrollment as well as college fixed effects to control for these differences in student composition. Pell receipt conditional on Pell eligibility (as defined above) is more than 20 percentage points higher among students in high-take-up colleges. This shows that there are large baseline differences across colleges in the top and bottom quartile of this measure.

Table 2.4. Summary Statistics for Take-Up Based Groups in the Pell Sample

Variable	Low-Take-Up Colleges	High-Take-Up Colleges
<u>Outcomes</u>		
Submitted FAFSA	0.497	0.557
	(0.500)	(0.497)
Received Pell Grant	0.237	0.403
	(0.425)	(0.491)
Received Pell Conditional on FAFSA Submission	0.472	0.704
	(0.499)	(0.456)
Received Pell Conditional on Pell Eligibility	0.616	0.836
	(0.486)	(0.370)
<u>Covariates</u>		
Hispanic	0.476	0.521
	(0.499)	(0.500)
White	0.221	0.276
	(0.415)	(0.447)
Asian	0.115	0.057
	(0.319)	(0.232)
Black	0.068	0.054
	(0.251)	(0.226)
Female	0.516	0.520
	(0.500)	(0.500)
Age	24.779	24.617
	(9.913)	(10.126)
Units Enrolled	8.347	9.234
	(4.974)	(4.881)
Sample Size	209,866	176,880
Number of Colleges	28	28

Notes: Standard deviations displayed in parentheses. Each observation represents a unique student observation in the 2017-18 baseline academic year. For duplicated student observations across terms and colleges, a single observation is selected at random.

Observe in Table 3 above that there does not appear to be a strong relationship between a college's baseline Pell take-up and its CS status. Pell receipt conditional on Pell eligibility is only four percentage points higher in non-CS colleges than in CS colleges. Thus, estimates of marginal SCFF effects in one grouping method should not be directly related to the other.

Main Estimation Results

ITS Estimates of Systemwide Effects

Table 5 presents ITS estimates from Equation (2). This model considers the SCFF's homogenous effects on aid awarding outcomes across the full sample of CCC colleges. By spring 2020, the fourth and final analytical term in which the SCFF was operational, the policy was associated with a 2 percentage point increase in a student's likelihood of Pell receipt. This effect represents a 6.4 percent increase relative to the baseline mean of 31.3 percent in 2017-18. This effect was driven by a 4.5 percentage point increase in likelihood of FAFSA submission, 8.6 percent of the baseline mean of 52.4 percent. It was also driven by a 3.6 percentage point increase in Pell receipt conditional on eligibility, 4.9 percent of the baseline mean of 73.8 percent. However, Pell receipt conditional on FAFSA exhibits a null effect. Finally, the policy was associated with a smaller, statistically insignificant 0.5 percentage point increase in likelihood of student Promise receipt, 0.9 percent of the baseline mean of 53.9 percent.

Table 2.5. ITS Results for Systemwide Effects: Model Coefficients and Linear Combinations to Represent Effects by Spring 2020

Variable or Effect	Pell Receipt	FAFSA Submission	Pell Receipt Conditional on FAFSA Submission	Pell Receipt Conditional on Eligibility	Promise Receipt
$Term_t$	-0.003***	-0.003***	-0.003***	-0.002	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$SCFF_t$	-0.016***	-0.002	-0.024***	-0.032***	-0.001
	(0.003)	(0.004)	(0.006)	(0.008)	(0.005)
$Terms\_Since\_SCFF_t$	0.009***	0.012***	0.004	0.017***	0.001
	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)
Total Effect by Spring 2020	0.020***	0.045***	-0.008	0.036***	0.005
	(0.006)	(0.008)	(0.010)	(0.012)	(0.009)
Mean of Y in Baseline Year	0.313	0.524	0.588	0.738	0.539
Sample Size	7,122,129	7,122,129	3,983,824	2,838,829	9,129,036
Number of Colleges	114	114	114	114	114

Notes: Each model controls for fall or spring term, student units, demographics, and college fixed effects. Standard errors shown in parentheses are clustered at the college level. A student is Pell-eligible if they submit a FAFSA with a Pell-eligible EFC and enroll in 6+ units in a given term. Baseline year statistics are computed for the 2017-18 academic year which preceded the SCFF. ***p<0.01, **p<0.05, *p<0.10.

Estimates of Heterogeneous Effects by CS Status

Next, I explore whether the CITS and event-study models report similar awarding gains when comparing effects across colleges that are financially affected (non-CS colleges) or unaffected (CS colleges) by aid incentives. I use the CITS to report both group-specific effects and net effects, the latter of which I compute as the difference between group-specific effects. I use the event-study model to report only net effects. Since the CS comparison group appears to offer a valid counterfactual, I consider these net effects to be analytically stronger than the group-specific effects reported by the CITS or the total effects reported by the ITS. However, it also carries a different interpretation. By differencing across groups, it ought to capture the specific effect of aid incentives. On the other hand, the ITS total effect or CITS group-specific effect does not difference across groups. These ought to capture the effects of incentives along with others related to an environment with lower-stakes accountability such as increased awareness of state goals.

Table 6 presents the CITS results from Equation (3). It reports the SCFF's effect by spring 2020. Table D1 presents the set of CITS coefficients from which I estimate this effect. By spring 2020, the SCFF was associated with an increase in Pell receipt among both financially-affected and financially-unaffected colleges. However, gains among financially-unaffected colleges slightly exceeded gains among financially-affected colleges. This results in an insignificant net decrease of .8 percentage points. As ITS results show, this effect for each group was driven by an increase in FAFSA submission and Pell receipt conditional on eligibility but not Pell receipt conditional on FAFSA submission. Correspondingly, financially-unaffected colleges increased FAFSA submission and Pell receipt conditional on eligibility by a greater margin than financially-affected colleges. By spring 2020, Promise receipt exhibited null gains among financially-affected colleges but increased by a significant 2.9 percentage points among financially-unaffected colleges. This resulted in a marginally significant net decrease of 2.7 percentage points for non-CS colleges relative to CS colleges by spring 2020.

Table 2.6. CITS Results with Financially-Affected and Financially-Unaffected College Groups: Linear Combinations to Represent Effects by Spring 2020

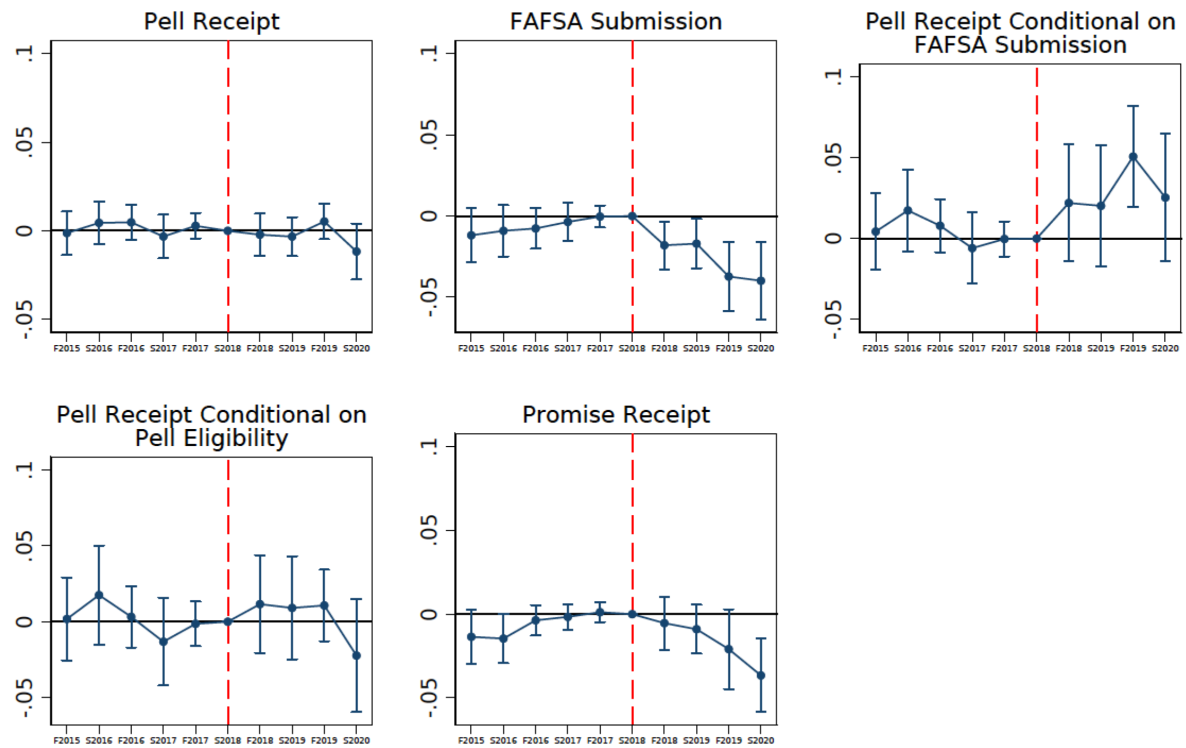
Variable or Effect	Pell Receipt	FAFSA Submission	Pell Receipt Conditional on FAFSA Submission	Pell Receipt Conditional on Eligibility	Promise Receipt
Effect on Financially-Affected (non-CS) Colleges by Spring 2020	0.019***	0.044***	-0.008	0.036***	0.002
	(0.006)	(0.009)	(0.011)	(0.013)	(0.010)
Effect on Financially-Unaffected (CS) Colleges by Spring 2020	0.028***	0.070***	-0.017	0.046**	0.029**
	(0.009)	(0.012)	(0.017)	(0.021)	(0.012)
Net Effect by Spring 2020	-0.008	-0.026*	0.009	-0.010	-0.027*
	(0.011)	(0.014)	(0.020)	(0.024)	(0.015)
Mean of Y in Baseline Year among Financially-Affected (non-CS) Colleges	0.320	0.533	0.591	0.675	0.551
Sample Size	7,122,129	7,122,129	3,983,824	2,838,829	9,129,036
Number of Colleges	114	114	114	114	114

Notes: Each model controls for fall or spring term, student units, demographics, and college fixed effects. Standard errors shown in parentheses are clustered at the college level. A student is Pell-eligible if they submit a FAFSA with a Pell-eligible EFC and enroll in 6+ units in a given term. Baseline year statistics are computed for the 2017-18 academic year which preceded the SCFF. ***p<0.01, **p<0.05, *p<0.10.

The result that financially-unaffected college increased awarding by an equal or greater amount than financially-affected colleges is unexpected. It suggests that colleges did not increase awarding because of financial pressure from the state. Rather, the SCFF and/or the related *Vision for Success* may have increased awarding systemwide because they emphasized the state's goal of increasing support for low-income students. In this case, a college's perception of how the SCFF would affect its revenue would not have changed its awarding behavior because it was responding to the state's signal of its priorities rather than to a change in incentives.

Figure 4 presents event-study results from Equation (4) using the same grouping method. Each coefficient captures the difference in college groups in a given lead term less that difference in spring 2018, the final term which preceded the SCFF. Vertical bars represent 95 percent confidence intervals for each coefficient. Lead coefficients for each outcome are not statistically significant. This implies that pre-SCFF, there were not substantial time-varying effects in aid which differentially affected college groups. Further, these coefficients do not exhibit clear, non-linear patterns which suggests that the data supports the linear CITS model. Lag coefficients are largely null which confirms the net effects reported by the CITS. For Pell receipt, FAFSA submission, and Promise receipt, coefficients increase in magnitude over the SCFF's operational period and are either marginally significant or significant in the final two treated terms. If interpreted causally, this indicates the presence of lagged policy effects as gains among unaffected colleges grew over the SCFF's operational period.

Figure 2.4. Event-Study Results with Financially Affected and Unaffected College Groups



Notes: Each point estimate represents the difference between financially affected (non-CS) and unaffected (CS) colleges in a given term less that difference in spring 2018. Each model includes controls for a student's demographics and number of enrolled units as well as college fixed effects. Vertical bars represent 95% confidence intervals with standard errors clustered at the college level. "F" and "S" respectively denote the fall and spring term in a given year.

Estimates of Heterogeneous Effects by Baseline Pell Take-Up

Finally, I present CITS and event-study results for college groups with high and low baseline Pell take-up. I measure take-up as the proportion of college students who receive a Pell Grant relative to those who appear to meet all Pell eligibility requirements, including enrolling in at least six units and submitting a FAFSA with an eligible EFC. Groups are comprised of colleges in the top and bottom quartile of this measure in 2017-18, respectively. I expect that this alternate grouping method will reveal a stronger net effect since a low-take-up college ought to be able to increase awarding by a greater margin.

To see why this is, consider the mechanisms through which a college may boost Pell awarding: Increasing application among students who have previously not used aid and/or increasing receipt among students who have previously applied for aid but did not receive it. A college in either group may similarly increase awarding through FAFSA submission by increasing advising or outreach to students who have not previously applied for aid. However, a low-take-up college ought to earn higher awarding returns by focusing on receipt conditional on FAFSA submission than a high-take-up college. With a larger number of eligible non-recipients, this mechanism may offer "low-hanging fruit" to this college since it is relatively easy to increase receipt among students who have already demonstrated eligibility. For instance, a college may increase awareness of benefits (e.g., through text or email reminders) among eligible students.

Table 7 presents the CITS results from Equation (3). It reports the SCFF's effect by spring 2020 across high- and low-take-up colleges as well as the net effect. Appendix Table D2 presents the set of CITS coefficients from which I estimate these effects. Again, note that group-specific effects should be interpreted with caution.

Table 2.7. CITS Results with Take-Up Based Treatment and Control Groups: Linear Combinations to Reflect Effects by Spring 2020

Variable or Effect	Pell Receipt	FAFSA Submission	Pell Receipt Conditional on FAFSA Submission	Pell Receipt Conditional on Eligibility
Effect on Low-Take-Up Colleges by Spring 2020	0.050***	0.024	0.076***	0.134***
	(0.010)	(0.018)	(0.016)	(0.021)
Effect on High-Take-Up Colleges by Spring 2020	-0.016	0.036***	-0.073***	-0.054
	(0.017)	(0.011)	(0.027)	(0.033)
Net Effect by Spring 2020	0.066***	-0.012	0.149***	0.188***
	(0.019)	(0.022)	(0.031)	(0.039)
Mean of Y in Baseline Year among Low-Take-Up Colleges	0.237	0.497	0.472	0.616
Sample Size	2,991,833	2,991,833	1,677,713	1,232,594
Number of Colleges	56	56	56	56

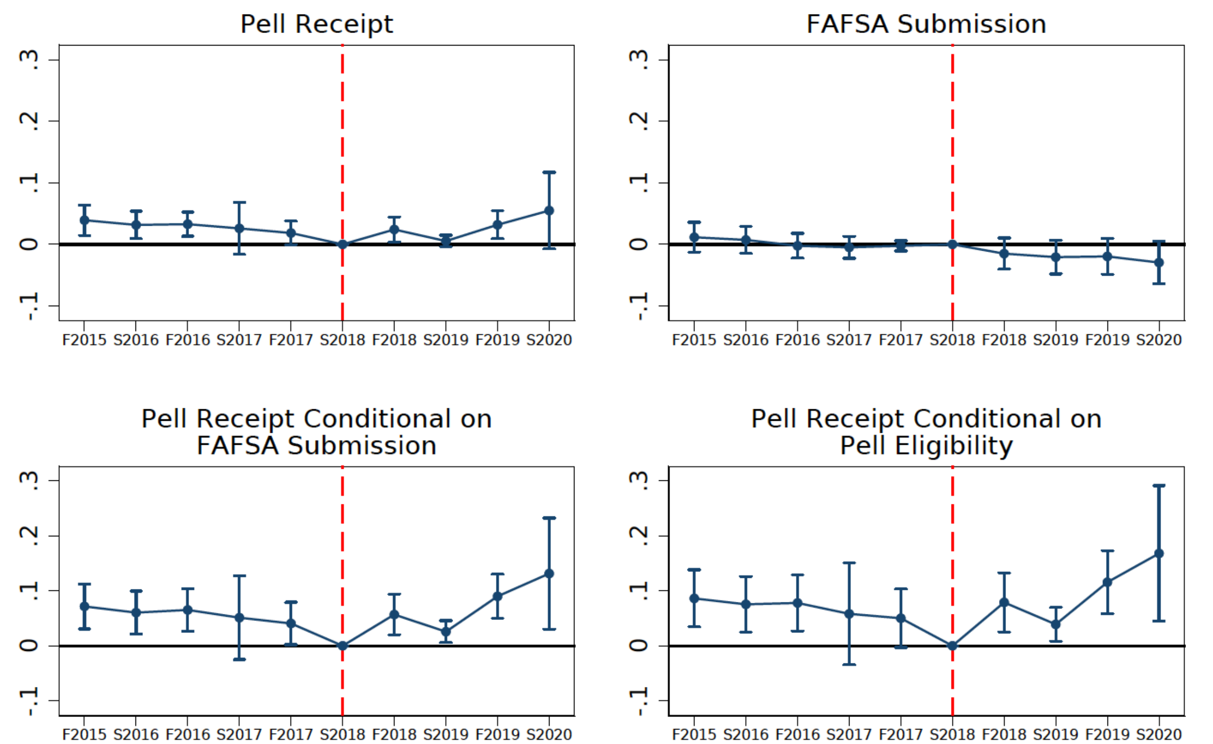
Notes: Each model controls for fall or spring term, student units, demographics, and college fixed effects. Standard errors shown in parentheses are clustered at the college level. A student is Pell-eligible if they submit a FAFSA with a Pell-eligible EFC and enroll in 6+ units in a given term. Baseline year statistics are computed for the 2017-18 academic year which preceded the SCFF. ***p<0.01, **p<0.05, *p<0.10.

By spring 2020, the SCFF was associated with a 5 percentage point increase in Pell receipt among low-take-up colleges. This represents a substantial 21.1 percent of the treatment baseline mean of 23.7 percent in 2017-18. Among high-take-up colleges, this effect was negative and null. This resulted in a net increase of 6.6 percentage points in Pell receipt for low-take-up colleges relative to high-take-up colleges. This effect was driven by Pell receipt conditional on FAFSA submission and Pell receipt conditional on eligibility. Receipt conditional on FAFSA increased by 7.6 percentage points among low-take-up colleges and decreased by 7.3 percentage points among high-take-up colleges. This resulted in a net increase of 14.9 percentage points effect for low-take-up colleges relative to high-take-up colleges. Receipt conditional on eligibility increased by 13.4 percentage points among low-take-up colleges and decreased by 5.4 percentage points among high-take-up colleges, the latter of which was not statistically significant. This resulted in a net increase of 18.8 percentage points for low-take-up colleges relative to high-take-up colleges. Finally, while FAFSA submission did increase among high-take-up colleges by a significant 3.6 percent, this mechanism did not result in increased Pell receipt for these colleges.

These results illustrate why low-take-up colleges were able to make awarding gains in response to aid incentives while high-take-up colleges were not. Rather than targeting FAFSA submission, low-take-up colleges increased Pell receipt by improving their Pell administration among filing and eligible students. This increase among eligible students was nearly twice the increase among FAFSA filers, indicating that colleges geared reforms toward this student group in particular. For high-take-up colleges, Pell awarding rates decreased among both filing and eligible students with mixed significance. This indicates that because these colleges were already excelling in administering Pell Grants to these student groups prior to the SCFF, they may have been constrained by "ceiling effects". That is, despite the increase in FAFSA submission, they were unable to increase awarding beyond pre-SCFF levels.

Figure 5 presents event-study results from Equation (4). Each coefficient estimates the difference in outcome between low- and high-take-up colleges in a given term less the difference in spring 2018. While lead coefficients for Pell receipt (conditional or unconditional) are largely significant, coefficients for each outcome exhibit a clear, linear trend. This suggests that the CITS results for this grouping method are valid since the time-varying differences across groups ought to be captured by linear estimation of pre-SCFF trends. The lag coefficients confirm the sign of each CITS net effect. Further, they indicate that college responses lagged the SCFF's adoption since the magnitude of each coefficient increases over the SCFF's operational period.

Figure 2.5. Event-Study Results with Take-Up-Based Treatment and Control Groups



Notes: Each point estimate represents the difference in outcome between treatment (low Pell take-up) and control (high Pell take-up) colleges ina given term less that difference in spring 2018. Each model includes controls for a student's demographics and number of enrolled units as well as college fixed effects. Vertical bars represent 95% confidence intervals with standard errors clustered at the college level. "F" and "S" respectively denote the fall and spring term in a given year.

Discussion

I find that the SCFF increased Pell awarding but not Promise awarding across the CCC system. By its fourth operational term, the policy was associated with a 2 percentage point increase in a student’s likelihood of receiving a Pell Grant. This effect was driven by an increase in FAFSA submission and Pell receipt conditional on eligibility but not Pell receipt conditional on FAFSA submission. Thus, systemwide colleges made Pell awarding gains by increasing application rates and improving take-up rates among Pell-eligible students.

While I do not find evidence that heterogeneity in awarding effects across colleges was driven by the SCFF's financial incentives, I do find strong heterogeneity by a college's baseline Pell take-up. The policy was associated with a 6.6 percentage point greater increase in Pell receipt among low-take-up colleges relative to high-take-up colleges. Low-take-up colleges achieved higher awarding gains by increasing Pell receipt among filing and eligible students, a mechanism which was less accessible to high-take-up colleges.

The null effect of the SCFF's aid incentives is surprising given the policy's positive effect on systemwide Pell awarding. There are two important aspects of the policy which may help explain this. First, the SCFF's rollout was rapid. It was signed into law in summer 2018, before which colleges had little information regarding formula metrics and incentives. This gave colleges little time to implement reforms in response to incentives prior to the 2018-19 academic year. Thus, the two post-SCFF years included in my analysis may be insufficient to detect aid effects. Unfortunately, the impact of Covid-19 may not permit the use of time series models to explore policy effects in later terms.

Second, while the SCFF's aid incentives were fairly strong, comprising 20 percent of an average district's apportionment revenue, the policy's hold harmless provision may have mitigated the urgency administrators felt to reform financial aid practices. This provision provided each district a two-year period in which its per-student apportionment revenue could not fall below its pre-SCFF level. It likely dampened the strength of the policy's incentives since districts could gain—but not lose—revenue resulting from awarding changes in this period.

Prior research helps reconcile the finding that SCFF effects were not driven by financial incentives. The relationship between institutional reform and performance funding in higher education may be explained by several "theories of action" (Dougherty & Reddy, 2011). One theory is that institutions respond to performance funding because of changes to its revenue. However, institutions may also respond because performance funding increases institutional awareness of state goals and competition among institutions for performance status. In the present policy context, the SCFF may have worked because of these latter mechanisms. That is, the SCFF clarified the state's emphasis on support for low-income students which it had previously articulated in its *Vision for Success* in 2017. Colleges appear to have responded to this signal by improving administration of Pell Grants, but this response did not depend on whether or not a college was financially affected by the SCFF's aid incentives.

The finding that colleges with lower baseline Pell take-up increased Pell awarding at a greater rate also appears in accordance with prior literature. College administrators often respond to performance incentives by targeting student metrics which may be increased in a quick and inexpensive manner (Dougherty & Reddy, 2011; Hillman et al., 2015, 2018; J. Ortagus et al., 2020). In the present policy context, administrators may have identified increased Pell awarding to eligible non-recipients as an efficient policy tool for increasing awarding.

In future work, I will examine the sensitivity of my ITS and CITS results to alternate analytical periods and coding practices. First, I will run models using an initial term of fall 2013, fall 2014, or fall 2016 as opposed to initial term of fall 2015 which I use in my models above. If model results are robust to alternate analytical periods, this would confirm that the reported policy effects are not driven by my choice of analytical period. Second, I will run models using a falsified SCFF coding practice wherein I code the policy to begin in one or two terms earlier than its actual implementation in fall

2018. If falsified results are null or lower in magnitude[84] than main results, this would show that reported policy effects are not driven by secular trends or other policies which began before or after the SCFF's implementation. Third, I will run models without the spring 2020 term in which student outcomes may be affected by the onset of Covid-19. I observe that counts of enrolled students and aid recipients in this decline from fall 2019 at a higher rate than in prior academic years. If exclusion of this term substantially increases reported policy effects, this may suggest that the reported policy effects are attenuated by Covid effects.

Conclusion

I use a variety of estimation strategies to show that the SCFF's incentives produced mixed effects on student financial aid receipt. The policy was associated with a 2 percentage point increase in student Pell receipt systemwide. This effect was driven by an increase in student application and an improvement in aid administration among eligible students. However, Promise receipt was unchanged by the policy. Surprisingly, colleges that were financially unaffected by the SCFF's aid incentives increased awarding at an equal or greater margin than colleges that were financially affected. Finally, colleges with lower baseline Pell take-up increased Pell awarding by a greater margin. This effect was driven by an increase in aid administration among filing and eligible students.

I conclude that while the SCFF boosted Pell receipt across the CCC, it was not the policy's financial incentives which prompted reform. Rather, state's increased emphasis

[84] Because this falsified coding strategy will code some non-SCFF terms as SCFF terms and some actual SCFF terms and SCFF terms, I expect that falsified models may report positive awarding effects, albeit with lower magnitude.

on support for low-income students across all colleges was a more likely catalyst for the observed increases in aid. In other words, the incentives yielded few gains net of an environment with lower-stakes accountability.

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Appendix A: Satisfactory Academic Progress

Introduction to Satisfactory Academic Progress

Federal guidelines instruct colleges to monitor whether each Pell Grant recipient meets SAP requirements (Federal Student Aid, 2019). While institutions have some discretion in setting SAP policy, these requirements typically include a minimum cumulative GPA, minimum cumulative percent units completed, and maximum timeframe of program completion (e.g., within 150 percent of the program's published length). A student who falls below any of these criteria in a given term based on their performance in prior terms fails to make SAP. They are subsequently placed on warning for one following term in which they are still eligible for a Pell Grant. If a student fails to make SAP in the warning period, they are placed on probation and lose Pell eligibility. Students may appeal this probation to receive aid in one more term. An institution may approve the appeal under varying extenuating circumstances (e.g., injury or illness).

CCC colleges determine Pell Grant eligibility using this SAP framework. While Promise Grant eligibility is not bound by federal guidelines, colleges use a similar set of SAP requirements for this grant (CCCCO, 2019d). Below, I review my process for flagging students who appear to miss SAP requirements for the Pell or Promise grant and dropping them from the respective samples.

Coding SAP Requirements for Pell Eligibility

I review CCC college policies and find some dissimilarity in SAP criteria for the Pell Grant. While each college appears to set a minimum cumulative 2.0 GPA and 67 percent completed units requirement, it may set either a 120 percent or 150 percent maximum timeframe requirement. These latter two requirements imply that if a student is pursuing a 60-unit associate degree, they are ineligible for a Pell Grant in a given term if their cumulative units attempted toward their degree in prior terms exceeds 90 or 120 units, respectively. I also find that each college uses a single-term warning period and probation period. However, colleges guidelines regarding a student's petition of probation and regaining of eligibility vary.

Further, each college appears to use all available course information to determine whether a student meets SAP. While difficult to interpret, this seems to imply that colleges within districts may share student records with one another to determine SAP. Further, if a student transfers credits from one college to another, the receiving college ought to have the student's records from the sending college, whether or not these two colleges are in the same district.

Based on these findings, I flag a student as failing to make SAP in a given term if their cumulative GPA falls below 2.0, percent units completed falls below 67 percent, or total units attempted toward their degree exceeds 90 in at least two prior terms. Once a student fails to make SAP in at least two total terms, I drop them from my sample in all terms following the second failing term. I generate each cumulative variable using a student's full course history at any CCC college. My decision to use the 90-unit requirement as opposed to the 120-unit requirement and considering a student's full course history are intentionally conservative. I reason that it is preferable to incorrectly flag eligible students as ineligible than to incorrectly flag ineligible students as eligible. The former would result in my dropping an increased number of students from the sample without a clear effect on model estimates. However, the latter would result in a larger sample with more students who are not eligible for Pell grants. In turn, this may reduce the precision of the SCFF's estimated effect on Pell receipt.

Coding SAP Requirements for Promise Eligibility

I review CCC college policies and find uniformity in SAP criteria for the Promise Grant. A student fails to make SAP in a single term if their cumulative GPA falls below a 2.0 or cumulative percent units completed falls below 50 percent. If a student fails to meet one or both criteria in two consecutive terms, they lose Promise Grant eligibility in future terms. Colleges appear to provide varying exceptions and petitions for students to regain eligibility (e.g., improving academic performance). While I do not document whether colleges use a student transfer records from other colleges to make SAP determinations for the Promise Grant, I reason that they are likely do so since they use these records to make SAP determinations for the Pell Grant.

Based on these findings, if a student fails to meet either the cumulative GPA or cumulative completed units requirement in two consecutive terms, I drop them from my sample in all terms following the second failing erm. I generate each cumulative variable using a student's full course history at any CCC college. Like my coding decisions for flagging students ineligible for Pell, these are intentionally conservative and are likely to incorrectly flag some eligible students as ineligible.

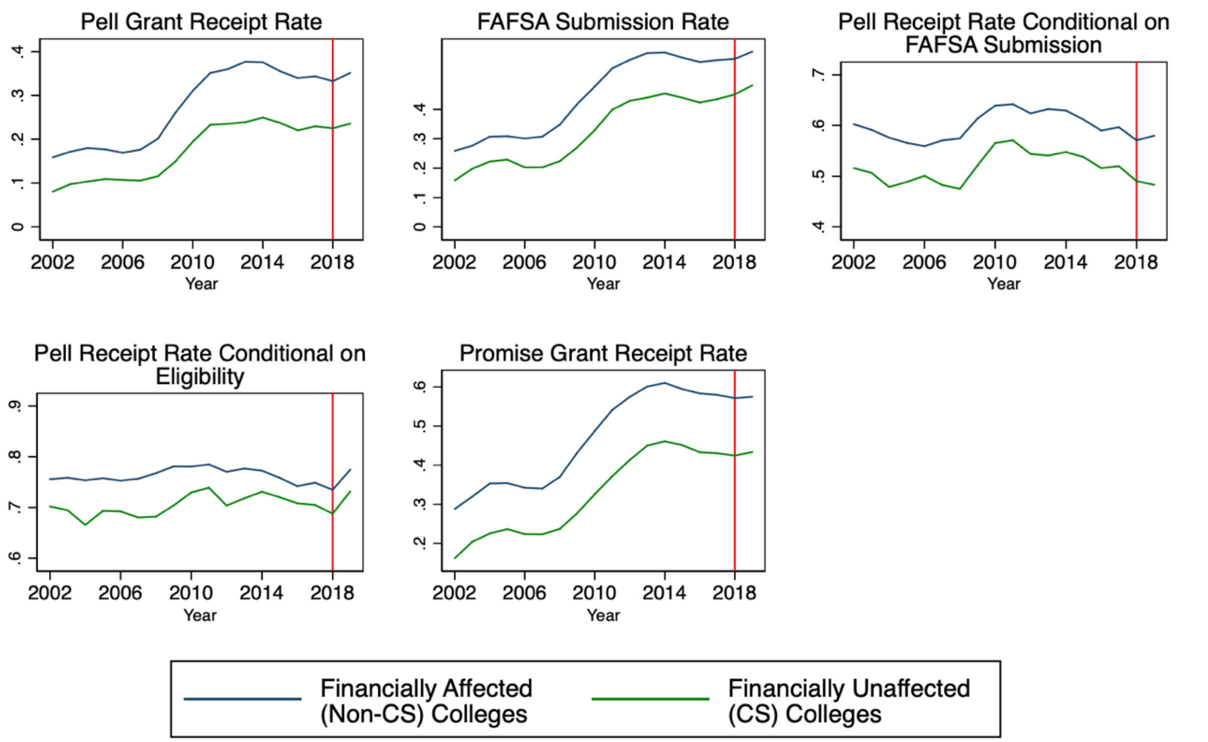
Appendix B: Common Trends by CS Status and Baseline Pell Take-Up

In each CITS and event-study model presented above, a primary validity threat is a change in awarding behavior that varies across groups and over time. If this effect is contemporaneous but unrelated to the SCFF, the estimated policy effects will be biased. Since I cannot observe counterfactual college outcomes in the absence of the SCFF, I cannot tell whether these model confounds exist. However, I present evidence here that awarding behavior is highly comparable across groups over time. This shows that historically, there have not been policies or secular trends that differentially affect college awarding which suggests that these are unlikely to be present in the analytical period.

Figure B1 presents trends in each of the four model outcomes across CS status which I use in my first grouping method. Each trend line shows an average group outcome weighted by the number of students in that group's colleges. Note two differences in sampled colleges and years in this exercise relative to the analytical samples described above. First, compared to the analytical period of 2015-2019, I leverage a longer 2002-2019 period in which term-level financial aid application and award data are available. This ought to provide more information on differential awarding behavior over time. Second, I drop colleges from this sample which were not operational or which do not appear to administer financial aid[85] over the full 2002-2019 period. This ensures that time trends are not driven by new colleges entering the CCC or by outliers. The final sample for this exercise is comprised of a balanced panel of 102 total colleges (14 CS and 88 non-CS) for Pell and FAFSA outcomes and 108 total colleges (15 CS and 93 non-CS) for the Promise outcome.

[85] For instance, I find several college-year outliers with no Pell recipients or FAFSA filers. For these outcomes, I drop these colleges from my sample entirely.

Figure 2.B1. Trends in Aid Outcomes Across CS and non-CS Colleges

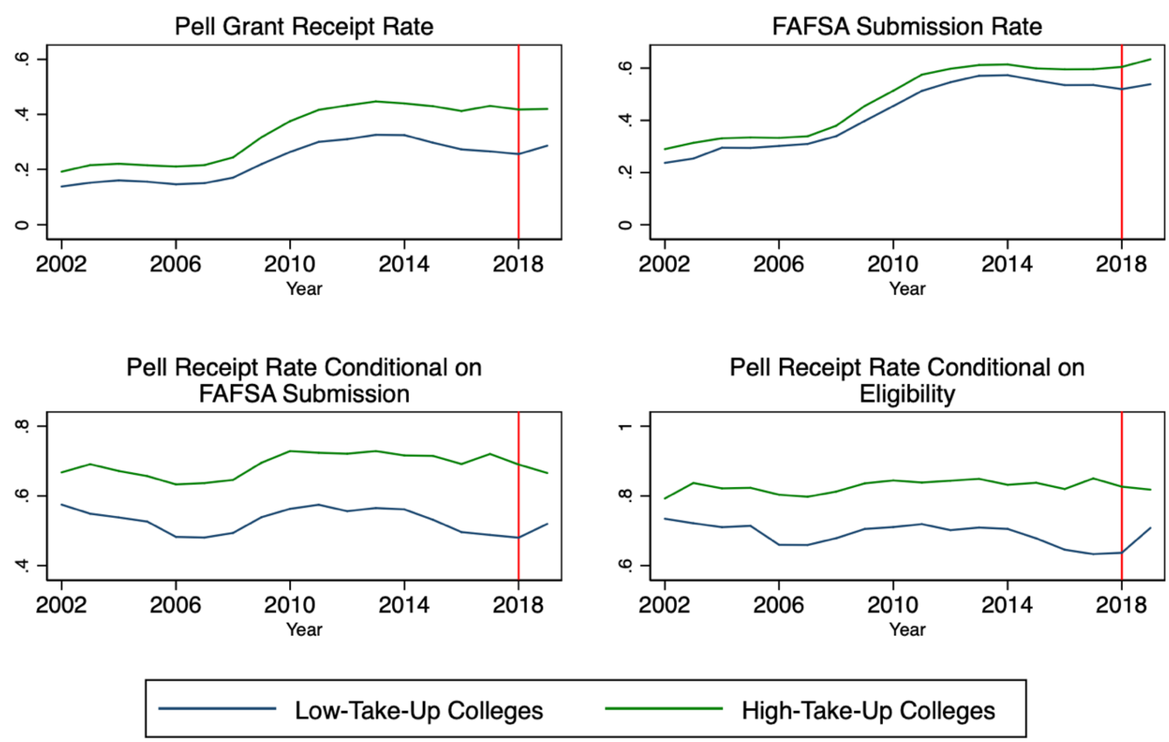


Notes: Rates are computed as the proportion of recipients or filers among sampled students. Each point represents the average rate in CS or non-CS colleges weighted by the number of sampled students in each college. A student is Pell-eligible if they submit a FAFSA with a Pell-eligible EFC and enroll in 6+ units in a given term. Sampled colleges in each figure represent a balanced panel of colleges which record student aid recipients in the full 2002-2019 period. For Pell and FAFSA outcomes, this includes 102 total colleges with 14 CS and 88 non-CS colleges. For Promise, this includes 108 tot colleges with 15 CS and 93 non-CS colleges. The vertical line marks the SCFF's first operational year.

Trends in Pell receipt (conditional or unconditional), FAFSA submission, and Promise receipt appear highly similar across CS and non-CS colleges over this two-decade span. An exception is that in the years following the Great Recession, Pell receipt and FAFSA submission rates increased at a slightly higher rate among non-CS colleges relative to CS colleges. Further, the Pell receipt rate conditional on FAFSA submission and the Pell receipt rate conditional on eligibility exhibit more year-to-year variability than the other outcomes but do not exhibit clear differential trends over time. I conclude that on the whole, there are not trends which differentially affect college groups over time. In turn, it appears appropriate to estimate SCFF effects by comparing awarding outcomes across CS and non-CS colleges.

Figure B2 presents the same set of results for my second grouping method of colleges in the top and bottom quartile of baseline Pell take-up. I omit the Promise outcome from this figure since I do not explore this outcome in analytical models that use this grouping method. Following the sampling method used for Figure A1, I use a balanced panel of colleges which are operational and award Pell Grants over the same two-decade period. The final sample for this exercise is comprised of a balanced panel of 51 total colleges (25 low-take-up and 26 high-take-up). Trends in each outcome again appear highly comparable over this period. This suggests that it is also appropriate to estimate SCFF effects using this second grouping method.

Figure 2.B2. Trends in Aid Outcomes Across High and Low Take-Up Colleges



Notes: Rates are computed as the proportion of recipients or filers among sampled students. Each point represents the average rate in high- or low-take-up colleges weighted by the number of sampled students in each college. A student is Pell-eligible if they submit a FAFSA with a Pell-eligible EFC and enroll in 6+ units in a given term.Sampled colleges in each figure represent a balanced panel of colleges which record student aid recipients in the full 2002-2019 period. This includes 51 total colleges with 25 low take-up gap and 26 high take-up gap colleges. The vertical line marks the SCFF's first operational year.

Appendix C: Alternate CS Grouping Method

In practice, the incentives of CS and non-CS districts may not be categorized in binary as I describe them above. Rather, a district may be more or less treated by incentives depending on how close it lies to the CS threshold. A district that narrowly makes CS status may be "mildly treated". This is because it may gain actual revenue from increased awarding as long as this dollar increase exceeds the small gap between its funding floor and local revenue. Conversely, a district that narrowly misses CS status may also be mildly treated. While it may gain actual revenue by increasing aid recipients at any margin, it also faces limited losses from failing to enroll high levels of aid recipients since its actual revenue cannot fall below its local funding level.

To account for these districts which may be mildly treated, I code a district as CS if its local revenue represents 90 percent or more of its funding floor in the year prior to the SCFF's implementation. I present summary statistics, CITS, and event-study results using this alternate grouping method. I find that these results are highly similar to the grouping method I use for the main set of CS models in which I use the 100 percent CS threshold. This is because there are only three additional colleges added to the CS group in this alternate coding practice.

Table A1, Table A2, and Figure A3 present summary statistics, CITS, and event-study results for this alternate grouping method, respectively. I compare a brief summary of the difference in CITS results here without further interpretation below. Pell receipt effects are highly similar to main results. FAFSA submission decreases slightly for financially unaffected colleges and increases by about 2 percentage points for financially affected colleges, resulting in a larger net effect. Promise receipt increases slightly for financially affected colleges and increases by 2 percentage points for financially unaffected colleges, resulting in a larger net effect that is statistically significant.

Table 2.C1. Summary Statistics for CS-Based Groups in the Pell and Promise Sample

Variable	Pell Sample Non-CS Colleges	Pell Sample CS Colleges	Promise Sample Non-CS Colleges	Promise Sample CS Colleges
<u>Outcomes</u>				
Submitted FAFSA	0.539	0.399	--	--
	(0.498)	(0.490)		
Received Pell Grant	0.324	0.215	--	--
	(0.468)	(0.411)		
Received Pell Conditional on FAFSA Submission	0.592	0.539	--	--
	(0.491)	(0.499)		
Received Pell Conditional on Pell Eligibility	0.674	0.653	--	--
	(0.469)	(0.476)		
Received Promise Grant	--	--	0.558	0.391
			(0.497)	(0.488)
<u>Covariates</u>				
Asian	0.087	0.177	0.086	0.171
	(0.282)	(0.381)	(0.281)	(0.376)
Black	0.059	0.028	0.057	0.027
	(0.236)	(0.165)	(0.233)	(0.162)
Hispanic	0.485	0.321	0.470	0.301
	(0.500)	(0.467)	(0.499)	(0.459)
White	0.266	0.347	0.278	0.373
	(0.442)	(0.476)	(0.448)	(0.484)
Female	0.517	0.518	0.528	0.544
	(0.500)	(0.500)	(0.499)	(0.498)
Age	24.362	23.597	26.295	26.961
	(9.779)	(9.485)	(11.052)	(12.157)
Units Enrolled	8.922	9.512	8.266	8.391
	(4.773)	(4.838)	(4.806)	(4.773)
Sample Size	771,018	91,171	979,002	126,642
Number of Colleges	99	15	99	15

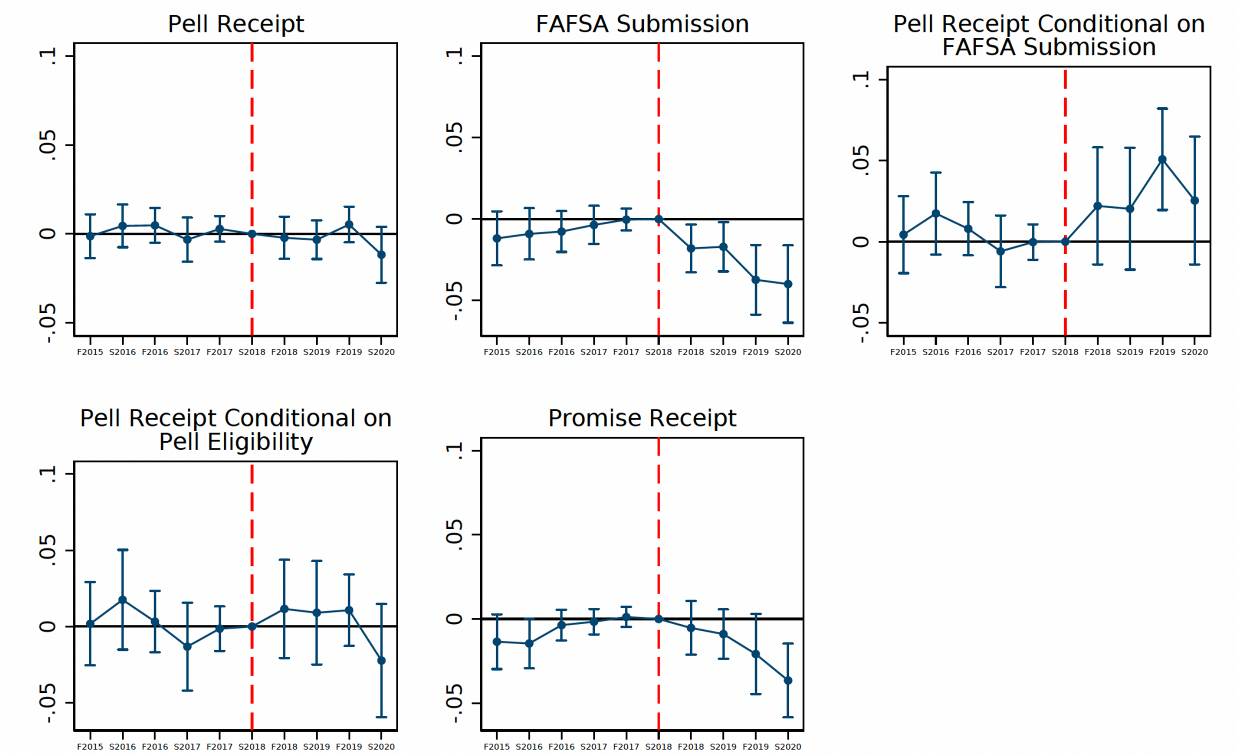
Notes: Standard deviations displayed in parentheses. Each observation represents a unique student observation in the 2017-18 baseline academic year. For duplicated student observations across terms and colleges, a single observation is selected at random.

Table 2.C2. CITS Results with Financially Affected and Unaffected College Groups: Linear Combinations to Represent Effects by Spring 2020

	Pell Receipt	FAFSA Submission	Pell Receipt Conditional on FAFSA Submission	Pell Receipt Conditional on Eligibility	Promise Receipt
Effect on Financially-Affected (non-CS) Colleges by Spring 2020	0.019***	0.040***	-0.004***	0.036***	-0.001
	(0.006)	(0.009)	(0.011)	(0.013)	(0.010)
Effect on Financially-Unaffected (CS) Colleges by Spring 2020	0.025***	0.092***	-0.053**	0.035*	0.049***
	(0.007)	(0.015)	(0.022)	(0.019)	(0.014)
Net Effect by Spring 2020	-0.006	-0.053***	0.049**	0.002	-0.0502***
	(0.009)	(0.017)	(0.025)	(0.023)	(0.017)
Mean of Y in Baseline Year among Financially-Affected (non-CS) Colleges	0.324	0.539	0.592	0.674	0.558
Sample Size	7,122,129	7,122,129	3,983,824	2,838,829	9,129,036
Number of Colleges	114	114	114	114	114

Notes: Each model includes seasonal (i.e., fall or spring term), demographic, and enrolled units controls as well as college fixed effects. Standard errors shown in parentheses are clustered at the college level. Baseline year statistics are computed for the 2017-18 academic year which preceded the SCFF. ***p<0.01, **p<0.05, *p<0.10.

Figure 2.C1. Event-Study Results with CS-Based Treatment and Control Groups



Notes: Each point estimate represents the difference between financially affected (non-CS) and unaffected (CS) colleges in a given term less that difference in spring 2018. Each model includes controls for a student's demographics and number of enrolled units as well as college fixed effects. Vertical bars represent 95% confidence intervals with standard errors clustered at the college level. "F" and "S" respectively denote the fall and spring term in a given year.

Appendix D: CITS Coefficients Used to Estimate Total Effects by Spring 2020

Table 2.D1. CITS Results with Financially Affected and Unaffected College Groups

Variable	Pell Receipt	FAFSA Submission	Pell Receipt Conditional on FAFSA Submission	Pell Receipt Conditional on Eligibility	Promise Receipt
$Term_t$	-0.003**	-0.003**	-0.004	-0.002	-0.006***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
$SCFF_t$	-0.013	0.001	-0.031	-0.046*	-0.010***
	(0.009)	(0.006)	(0.026)	(0.025)	(0.003)
$Terms\_Since\_SCFF_t$	0.010***	0.017***	0.004	0.023***	0.010***
	(0.003)	(0.002)	(0.007)	(0.007)	(0.003)
$Term_t$ x $Treat_s$	-0.0001	0.0003	0.0003	0.0003	0.0020
	(0.002)	(0.002)	(0.003)	-(0.003)	(0.002)
$SCFF_t$ x $Treat_s$	-0.003	-0.003	0.007	0.014	0.010*
	(0.009)	(0.007)	(0.027)	-(0.027)	(0.006)
$Terms\_Since\_SCFF_t$ x $Treat_s$	-0.001	-0.006**	0.001	-0.006	-0.009**
	(0.004)	(0.003)	(0.008)	(0.008)	(0.004)
Mean of Y in Baseline Year among Financially Affected (non-CS) Colleges	0.320	0.533	0.591	0.675	0.551
Sample Size	7,122,129	7,122,129	3,983,824	2,838,829	9,129,036
Number of Colleges	114	114	114	114	114

Notes: Each model controls for fall or spring term, student units, demographics, and college fixed effects. Standard errors shown in parentheses are clustered at the college level. A student is Pell-eligible if they submit a FAFSA with a Pell-eligible EFC and enroll in 6+ units in a given term. Baseline year statistics are computed for the 2017-18 academic year which preceded the SCFF. ***p<0.01, **p<0.05, *p<0.10.

Table 2.D2. CITS Results with Take-Up Based Treatment and Control Groups

Variable or Effect	Pell Receipt	FAFSA Submission	Pell Receipt Conditional on FAFSA Submission	Pell Receipt Conditional on Eligibility
$Term_t$	-0.00001	-0.002	0.002	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
$SCFF_t$	-0.007	-0.004	-0.006	-0.014
	(0.016)	(0.008)	(0.025)	(0.032)
$Terms\_Since\_SCFF_t$	-0.002	0.010***	-0.017	-0.010
	(0.008)	(0.003)	(0.012)	(0.015)
$Term_t$ x $Treat_s$	-0.007**	-0.003	-0.012***	-0.015***
	(0.003)	(0.003)	(0.004)	(0.005)
$SCFF_t$ x $Treat_s$	-0.007	-0.006	-0.011	-0.003
	(0.019)	(0.013)	(0.031)	(0.042)
$Terms\_Since\_SCFF_t$ x $Treat_s$	0.018**	-0.002	0.040***	0.0478***
	(0.008)	(0.004)	(0.013)	(0.016)
Mean of Y in Baseline Year among Low-Take-Up Colleges	0.237	0.497	0.472	0.616
Sample Size	2,991,833	2,991,833	1,677,713	1,232,594
Number of Colleges	56	56	56	56

Notes: Each model controls for fall or spring term, student units, demographics, and college fixed effects. Standard errors shown in parentheses are clustered at the college level. A student is Pell-eligible if they submit a FAFSA with a Pell-eligible EFC and enroll in 6+ units in a given term. Baseline year statistics are computed for the 2017-18 academic year which preceded the SCFF. ***p<0.01, **p<0.05, *p<0.10.

Paper 3: Impact of Degree Incentives on Degree Production in the California Community College System

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Abstract

Performance funding (PF) policies are used across higher education systems in the United States as a means of raising the performance of institutions and students. These policies provide financial incentives for student outcomes that are prioritized by their adopting states. California recently adopted the Student-Centered Funding Formula (SCFF), a PF policy for the California Community College (CCC) system. The SCFF provides financial incentives for numerous student outcomes including certificate and degree completion. In this paper, I assess the SCFF's effects on certificate and degree production in the CCC system. I draw on student-level administrative data from the CCC system in the 2015-2018 period. I use an interrupted time series model to estimate systemwide effects and comparative interrupted time series models to estimate differential effects across college groups. Results show that the SCFF positively affected systemwide production of certificates and traditional associate degrees but not Associate Degrees for Transfer. There is some evidence that colleges that were more affected by the SCFF's financial incentives made greater awarding gains than colleges that were less affected.

Introduction

Performance funding (PF) policies have become prevalent in United States postsecondary education in recent decades (Dougherty & Reddy, 2011; J. C. Ortagus et al., 2020; Rabovsky, 2012; Rosinger et al., 2020). States that adopt PF policies aim to encourage improvement in student outcomes by tying a portion of an institution's funding to its performance on state-set metrics. Common metrics include student graduation, retention, and job placement.

Prior research shows that PF policies often fail to improve student outcomes relative to enrollment-based funding policies in both two-year and four-year institutions (J. C. Ortagus et al., 2020). In the community college setting, PF policies adopted nationwide are not associated with an increase in associate degree completion, on average (Li & Kennedy, 2018; Tandberg et al., 2014). States that adopt policies with a large proportion of funding tied to institutional performance may exhibit gains in certificate completion (Hillman et al., 2015, 2018; Li & Kennedy, 2018).

California recently adopted the Student-Centered Funding Formula, a PF policy that appropriates funds for its huge network of public community colleges, the California Community Colleges (CCC). The SCFF aims to encourage growth in degree production and a reduction in achievement gaps in the CCC system. It does so by paying a district for its counts of students who achieve any of nine outcomes, including attainment of a certificate and associate degree. It also pays a district a premium rate for the outcomes achieved by students who are financial aid recipients.

In this paper, I assess whether the introduction of the SCFF increased certificate and degree production in the CCC system in its first operational year. I employ a series of analytical strategies to estimate policy effects. I use interrupted time series (ITS) models to estimate systemwide policy effects. I find that the SCFF is associated with gains in certificates but not associate degrees.

I also use comparative interrupted time series (CITS) models with two distinct grouping methods to estimate effects across colleges that ought to have been more or less financially affected by the SCFF's degree incentives. The first method leverages the fact that while most colleges experienced a change in financial incentives resulting from the SCFF, a subset of colleges did not because they are locally funded and thus don't receive apportionment revenue from the state. I find that there were not substantial differences in awarding changes across the two colleges groups.

The second method leverages variability in a college's baseline proportion of financial aid recipients. Colleges with a higher proportion of aid recipients ought to have higher degree incentives since the SCFF pays a premium rate for degrees awarded to these students. Again, I find that the two groups exhibit similar changes in awarding as a result of the SCFF.

My results suggest that SCFF's financial incentives were not the catalyst for increased certificate and degree production in the CCC system, per se. Rather, the state's emphasis on degree completion, which was lower-stakes, appears to be a more likely driver of increased certificate and associate degree awarding.

Background

Performance Funding in Higher Education

Over the past three decades, the use of PF policies has sharply increased across 2-year community colleges and 4-year universities in the United States (Dougherty & Reddy, 2011; Rabovsky, 2012). The first wave of PF policies began in the late 1990s and early 2000s alongside an increase in accountability reforms across the public sector such as No Child Left Behind (Dougherty & Reddy, 2011; Rabovsky, 2012). These policies typically included performance pay that adopting states allocated across institutions as bonuses above their base funds (Dougherty & Reddy, 2011). Performance funds often represented a small portion of total state appropriations (e.g., less than five percent) and were allocated on the basis of long-run student success outcomes including such as retention, graduation, and job placement (Dougherty & Reddy, 2011; J. C. Ortagus et al., 2020).

Many states abandoned these policies in the 2000s as their political support waned (Dougherty & Reddy, 2011; Rabovsky, 2012). This resulted from limited performance gains and infeasibility of bonus pay amid tightening state budgets. However, a second wave of PF policies began in the late 2000s and early 2010s (Dougherty & Reddy, 2011; Rabovsky, 2012). This was facilitated by increased lobbying for higher education accountability among nonprofits and policy groups as well as an emphasis on college completion from the Obama administration.

These policies were characterized by stronger incentives than the first wave of PF policies. They included performance funds that represented a larger proportion of state support (e.g., a majority of state appropriations) (Dougherty & Reddy, 2011). These funds were also used to determine an institution's base funding. Institutions would thus face funding cuts for poor performance under these newer policies. These policies also included more nuanced student performance metrics. On top of the long-run outcomes included in the earlier wave, newer outcomes often included intermediate student outcomes such as completion of collegiate-level math or English and reaching a specified threshold of completed units.

In total, 41 states have adopted PF policies at any point in time (J. C. Ortagus et al., 2020). Thirty of these states use a PF policy at the time of this report (Rosinger et al., 2020). These policies vary considerably in their number of operational years, adopted student success indicators, share of funding tied to performance, and whether they are used to fund publics colleges, universities, or both (J. C. Ortagus et al., 2020).

Theoretical Framework

A principal-agent model (Jensen & Meckling, 1976) is often used as a theoretical framework to demonstrate how a PF policy may produce its intended outcomes. In this model, a principal (a government) contracts with an agent (a college) to perform a service on its behalf (providing higher education). Each actor is assumed to be "revenue-maximizing" according to its set of financial incentives.

Under a traditional, enrollment-based funding policy, the incentives of a government and college may be misaligned (Hillman et al., 2015; J. C. Ortagus et al., 2020). For instance, a government may be primarily interested in enhancing its future workforce by providing students with requisite skills and credentials whereas a college may be primarily interested in maximizing its revenue from state funding and student tuition (Hillman et al., 2015). Since the college does not have a direct financial incentive to produce the government's desired outcomes, it may optimally respond by expending resources in ways that attract student enrollment but do not emphasize student achievement (e.g., building luxury dormitories).

A PF policy is theorized to work by aligning the college's financial incentives with the government's educational goals. This is achieved by paying the college for its performance according to student performance metrics defined by the government

(Hillman et al., 2015; J. C. Ortagus et al., 2020). Under this new funding policy, the college may optimally respond by expending resource to improve student performance along these metrics, thereby increasing its revenue from the state.

Prior Literature

Despite the prevalence of PF policies in higher education in the United States, a large body of literature offers limited evidence that these policies produce the institutional reforms that policymakers intend. Further, the unintended impacts of these policies may inhibit student achievement. Below, I briefly review qualitative results across the university and community college settings to explore the mechanisms through which a PF policy may encourage institutional reform. Next, I review qualitative results with a focus on literature from the community college setting since these are most relevant to the present paper.

Qualitative Results of PF Adoption

Dougherty and Reddy (2011) review qualitative findings on the impacts of PF policies across universities and community colleges. A PF policy may prompt institutional reform through several "theories of action" (Argyris, 1997). These include changes in funding induced by the policy, increased awareness of state goals for higher education, increased awareness of performance on state goals, and increased competition for performance status (Burke, 2020; Dougherty & Hong, 2006).

An institution may use several strategies to improve performance on state goals. These include increased data use in instructional planning, improvements in academic policies and practices (e.g., reduced class sizes, expanded degree offerings), and changes to student services (e.g., reduced barriers for student registration and graduation, increased advising services) (Bell, 2005; Burke, 2020; Morris, 2002).

However, several factors limit institutional responsiveness to a PF policy. These include skepticism regarding the validity of student metrics (e.g., the perception that metrics fail to capture true student achievement), inadequacy and instability of funding tied to performance, brief policy durations, varying understanding of funding mechanics across institutions, varying capacity to implement reforms across institutions, and "gaming the system" (Bell, 2005; Dougherty et al., 2012; Dougherty & Hong, 2006; Morris, 2002). This final effect refers to behavior in which an institution improves its performance on metrics in ways that are efficient but may not benefit student achievement (e.g., increased awarding of redundant degrees).

Finally, there are unintended impacts of PF policies that may hinder student success. These include increased compliance costs (e.g., shifting resources from instruction towards data collection), narrowed institutional missions (e.g., cutting programs which offer few financial incentives), weakened academic standards (e.g., reduced degree requirements, grade inflation), and "cream skimming" (Bell, 2005; Dougherty & Hong, 2006). This final effect refers to behavior in which an institution restricts admission of less prepared students to increase average student performance on state metrics.

Quantitative Results of PF Adoption among Universities

Quasi-experimental studies find limited gains in student outcomes resulting from PF policy adoption in the university setting (J. C. Ortagus et al., 2020). For instance, studies find null effects in bachelor degree completion associated with PF policies adopted in Tennessee and Ohio (Hillman et al., 2018; Ward & Ost, 2021), Pennsylvania (Hillman et al., 2014), Indiana (Umbricht et al., 2015), and across national Historically Black Colleges and Universities (Boland, 2018). Studies also find null effects in other common performance metrics including student retention (Favero & Rutherford, 2020; Ward & Ost, 2021) and graduation rates (Favero & Rutherford, 2020; Umbricht et al., 2015; Ward & Ost, 2021).

However, a few studies report positive PF policy impacts under more narrow outcomes or policy conditions. For instance, Li (2020) finds gains in STEM bachelor degree completion in states that include STEM incentives in their PF policies. Favero and Rutherford (2020) find gains in bachelor completion only among states that adopted stricter policies. Finally, Tandberg and Hillman (2014) find that gains in bachelor production that only emerge many years following policy adoption.

Studies also find evidence for unintended impacts of PF policies which may inhibit student success in the university setting (J. C. Ortagus et al., 2020). These include restricted admission among minority and/or low-income students (Birdsall, 2018; Umbricht et al., 2015) and increased resource gaps between more- and less-selective institutions that are driven by disproportionate performance gains among more-selective institutions (Hagood, 2019).

Quantitative Results of PF Adoption among Community Colleges

Quasi-experimental literature also offers limited evidence that PF policies promote student success in the community college setting (J. C. Ortagus et al., 2020). I review several studies in greater detail here since these are most relevant to the present paper. Each study uses difference-in-differences modeling in which colleges in states that adopt PF policies are compared to colleges in states that do not adopt PF policies.

Tandberg et al. (2014) evaluate the average and state-specific effects of PF policies on associate degree completion across 19 adopting states in the 1990-2010 period. They find null average effects in models that use three plausible control groups. However, these averages mask considerably heterogeneity across states. For instance, New Jersey and Washington State exhibited significant gains in completion across each control group in the range of 11 to 18 percent. Conversely, South Carolina and Texas exhibited significant losses in each model in the range of 7 to 15 percent. The remaining states either exhibit consistently null effects or variability in sign and significance across models and control groups. Thus, the authors find little evidence that PF policies boost associate degree completion nationwide but find ample evidence for variability in effects across state-specific policies.

Li and Kennedy (2018) similarly use a national sample consisting of 29 adopting states in the 1990-2013 period. They expand upon the findings of Tandeberg et al. by exploring heterogeneity in effect by degree type (certificates with expected completion time of less than one year or one-to-two years and associate degrees) and policy "strength" (e.g., the proportion of funding that a state ties to institutional performance). On average, they find null policy effects for each degree type. However, colleges treated by stronger policies exhibit significant gains in short certificate completion in the range of 37 to 71 percent and losses in associate degree completion in the range of 8 to 18 percent, each with mixed significance. Thus, colleges appear to respond to PF policies by prioritizing shorter-run student outcomes at the expense of longer-run student outcomes.

Hillman et al. (2018) assess changes in associate degree and certificate completion in Ohio and Tennessee in the 2005-2014 period. Each state adopted a "strong" PF policy in which at least 85 percent of a college's base funds were tied to performance pay[86]. The authors compare treated colleges to those in one of three plausible control groups. They find moderate evidence for certificate gains and associate degree losses in Ohio colleges. However, these effects are sensitive to the choice of control group and are null in some models. They find stronger evidence for certificate gains in Tennessee colleges. Certificate completion increased by 61 to 85 percent across control group models. Tennessee colleges exhibit null-to-negative associate degree effects which are sensitive to the choice of control group.

This observed tradeoff in shorter- and longer-run degrees suggests that certificate and associate degrees may act as substitutes (Hillman et al., 2018). That is, the increase in certificate completion is driven by students who would have otherwise earned associate degrees. If true, this outcome appears to contradict the intended impacts of a PF policy. While policymakers seek to enhance their state's workforce through increased student credentials (Dougherty & Reddy, 2011; Hillman et al., 2015), the earnings premium for a certificate is far lower than that of an associate degree (Belfield & Bailey, 2011, 2017). Thus, the PF policy may in fact hinder student success and workforce preparation.

Hillman et al. (2015) evaluate Washington State's PF policy in the 2002-2012 period. This policy is "weak" in that it tied less than one percent of college funds to performance. The authors explore changes in retention rates as well as completion of

[86] However, each state phased in performance pay over time. Further, Ohio adopted a hold harmless provision in the first several operational policy years. These may limit the strength of performance incentives.

short certificates (i.e., less than a year), long certificates (i.e., more than a year), and associate degrees. They find null effects in retention and associate completion across three control groups. They find moderate evidence for short certificate gains, although these effects have mixed significance and are highly sensitive to the choice of control group. They find stronger evidence for long certificate losses which are significant and range from 34 to 55 percent across control groups.

This quantitative literature casts doubt on whether the SCFF was likely to positively affect certificate and degree production in the CCC system. It illustrates that PF policies may be unlikely to produce substantially better student outcomes than enrollment-based funding policies. This is particularly true for policies like the SCFF which tie a relatively small proportion of funding to institutional performance (Hillman et al., 2015; Li & Kennedy, 2018). Further, in evaluating the SCFF's effects, it is crucial to examine the tradeoff between shorter and longer student degrees since there is moderate evidence that PF policies benefit production of shorter degrees at the expense of longer degrees (Hillman et al., 2015, 2018; Li & Kennedy, 2018).

California Community Colleges and the Student-Centered Funding Formula

The CCC system is a massive network of public community colleges which serves more than two million students annually (California Department of Finance, 2021). It consists of 73 districts which may contain one or multiple of the CCC system's 116 colleges. The state is primarily responsible for funding the CCC system (Smith, 2018). It uses a centralized funding formula to apportion state revenue across CCC districts.

In 2018-19, the state shifted its funding priorities for the CCC system by replacing an enrollment-based funding formula with the SCFF. The prior formula apportioned revenue on a per-student basis and weighted all students equally (Smith, 2018). The SCFF weights funding differently to fund higher-performing districts more highly. It does so by paying a district set rates for nine student success outcomes. These include student completion of a credit certificate that requires at least 16 units, traditional associate degree (henceforth, simply "associate degree"), or associate degree for transfer to a four-year university (ADT). These incentives also fund low-income students more highly. A district earns a higher rate for awarding a given degree to a student who is a Pell or Promise Grant[87] recipient than for awarding the same degree to a student who is not a recipient of either award.

Table 1 presents each student success metric and its corresponding rates for all students, Pell recipients, and Promise recipients. The state pays a district for its counts of students who achieve each outcome. For instance, a district earns $1,320 for each associate degree it awards. For each associate degree awarded to a Pell or Promise Grant recipient, a district earns an additional $500 and $333, respectively. It earns both premiums for awarding the degree to a student who receives both grants. On average, total revenue from the SCFF's degree incentives represent roughly 10 percent of a district's apportionment revenue. This rate is relatively low compared to PF policies in other states (Li & Kennedy, 2018).

Note that the SCFF also adopted incentives for financial aid awarding which represent an additional 20 percent of a district's apportionment revenue, on average. These incentives serve as the focus of *Paper 2: Impact of Financial Aid Incentives on Student*

[87] The California Promise Grant is a state-funded program that reduces financial barriers to the CCC system by waiving student tuition (CCCCO, 2019d).

Receipt in the California Community College System. For more detailed coverage on the SCFF's incentives and the mechanical differences between it and the prior formula, see *Paper 1: District Apportionment in the California Community College System.*

Table 3.1. Student Success Allocation Table

Outcome	Rate
All Students Schedule	
Associate degrees for transfer (ADT) granted	$1,760
Associate degrees granted (excluding ADTs)	$1,320
Baccalaureate degrees granted	$1,320
Credit certificates (16+ units) granted	$880
Completion of transfer-level mathematics and English courses within first academic year of enrollment	$880
Successful transfer to four-year university	$660
Completion of nine or more CTE units	$440
Attainment of regional living wage	$440
Pell Grant Students Schedule	
Associate degrees for transfer (ADT) granted	$666
Associate degrees granted (excluding ADTs)	$500
Baccalaureate degrees granted	$500
Credit certificates (16+ units) granted	$333
Completion of transfer-level mathematics and English courses within first academic year of enrollment	$333
Successful transfer to four-year university	$250
Completion of nine or more CTE units	$167
Attainment of regional living wage	$167
Promise Grant Students Schedule	
Associate degrees for transfer (ADT) granted	$444
Associate degrees granted (excluding ADTs)	$333
Baccalaureate degrees granted	$333
Credit certificates (16+ units) granted	$222
Completion of transfer-level mathematics and English courses within first academic year of enrollment	$222
Successful transfer to four-year university	$167
Completion of nine or more CTE units	$111
Attainment of regional living wage	$111

Source: CCCCO's 2018-19 Recalculation Apportionment.

The state's adoption of the SCFF ostensibly changed the financial incentives of CCC districts. Under the prior enrollment-based formula, a district maximized its apportionment by increasing total student enrollment. Under the SCFF, a district faces reduced incentives to increase total enrollment and new incentives to increase a variety of student success outcomes, including certificates, associate degree, and ADTs. Crucially, the SCFF's enacting legislation contained a hold harmless provision that protected district apportionment against losses in the first two policy years[88]. Thus, while a district could make revenue gains during this period, it could not lose revenue. This provision may have limited the SCFF's effects on degree production if it caused colleges and districts to respond to degree incentives with less urgency.

Some CCC districts do not receive apportionment revenue from the state's funding formula (Smith, 2018). These are known as "Community-Supported" (CS) districts. CS districts raise a higher amount of apportionment revenue through local taxation than what the state would otherwise provide through the funding formula. These districts retain local apportionment revenue but do not receive additional apportionment revenue from the state. While all districts, including CS districts, received the signal that the state was placing increased emphasis on the set of student outcomes incentivized by the SCFF, CS districts ought to have had no change in financial incentives from the new formula. I use CS status as one grouping method in my analytical models since colleges in non-CS districts[89] are financially affected by

[88] This hold harmless period was ultimately extended in subsequent legislation. However, in the first SCFF year, districts operated under the assumption of a two-year window.
[89] CS is technically a district-level status since the state apportions revenue at this level. However, for the remainder of the paper, I use this status to denote a district in the context of the state's apportionment process or a district's colleges in the context of grouping in my analytical models.

degree incentives whereas colleges in CS districts are financially unaffected. I discuss the difference in incentives between CS and non-CS colleges in more detail below.

Certificates, Associate Degrees, and ADTs

The credential offerings of CCC colleges include certificates, associate degrees, and ADTs (CCCCO, 2021b). Each degree type is offered in arts and science and across hundreds of subfields. Certificates vary in their number of required units and curricular focus (e.g., for credit or noncredit instruction) (Academic Senate for California, n.d.-b). The SCFF only provides financial incentives for credit certificates that require at least 16 units (CCCCO, 2020c). A full-time student enrolls in 15 units per semester and can complete a certificate in one or two years, depending on the number of units it requires.

Associate degrees and ADTs each require 60 degree-applicable units, 18 of which must be completed a student's area of emphasis (Academic Senate for California, n.d.-a). The expected time of completion of each degree is two years. However, many CCC students take substantially longer than expected to reach a given degree goal (Foundation for California Community Colleges, 2017). For instance, the average time to completion of an associate degree is 5.2 years.

ADTs were introduced in 2011 by the CCC system and California State University (CSU) systems to improve the process of student transfer from a community college to a four-year university (Wheelhouse, 2017). ADT recipients are guaranteed admission to a CSU system and may transfer their credits towards a CSU bachelor's degree with a similar curricular focus.

Research Questions

In the present study, I assess whether the financial incentives included in the SCFF's student success allocation improve certificate and degree production in the CCC system. Specifically, I address the following questions:

1. Does systemwide awarding of certificates, associate degrees, and ADTs increase following the adoption of the SCFF?
2. How does the effect in RQ1 vary by the extent to which a college is financially affected by degree incentives?
    a. Do non-CS colleges which are financially affected by degree incentives exhibit larger awarding gains than CS colleges which are financially unaffected?
    b. Do colleges that enroll more financial aid recipients which face higher degree incentives exhibit larger awarding gains than colleges that enroll fewer financial aid recipients which face lower degree incentives?

Data and Methods

Data Construction

I use administrative files from the CCCCO to construct a dataset that tracks annual, college-level counts of awarded certificates, associate degrees, and ADTs. These files contain rich student-level data for each student who attends the CCC system. I merge files that track annual degree information (e.g., attainment of each degree type) and term-level student characteristics (e.g., race, gender, age) and course information (e.g., units enrolled).

One key analytical variable that is not recorded by the CCCCO is a district's CS status. I use this variable to group colleges that are financially affected or unaffected by degree incentives. I use CCCCO apportionment data to flag a district as CS in a given year if its local tax revenues exceed the revenue that the state would have otherwise provided through the funding formula.

I use an analytical period of the 2015-16 through the 2018-19 academic year. This captures three years prior to and one year following the SCFF's implementation in fall 2018. I choose this period so that there are a sufficient number of pre-intervention data points to meet the requirements of a CITS model (Somers et al., 2013). I do not include the SCFF's second operational year in 2019-20 since the spring 2020 term marked the onset of the Covid-19 pandemic. I find in Figure A1 that course completion and degree attainment declined in this year, consistent with the expected effects from the pandemic. Thus, I exclude this year to prevent potential contamination of policy effects.

Analytical Samples

I construct samples at the college-year level for each of the certificate, associate degree, and ADT outcomes. Each sample includes college-years with positive counts of the corresponding degree. For a college with zero counts in one out of the three pre-SCFF years included in the analytical period, I drop that college-year but retain the college in the sample in years with non-zero counts. For colleges with zero counts in two or more of the three pre-SCFF years included in the analytical period, I drop that college from the sample entirely. Table 2 displays college counts across the three samples.

Table 3.2. Annual College Counts in the Certificate, Associate Degree, and ADT Samples

Year	Certificate Sample	Associate Degree Sample	ADT Sample
2015	113	114	111
2016	113	114	113
2017	114	114	113
2018	114	114	113

Note: Year denotes the fall of a corresponding academic year.

Degree Counts

To construct the outcomes of college-year counts of certificates, associate degrees, and ADTs, I collapse student-level degree files. I make no restrictions to generate college-year counts of associate degrees and ADTs. However, since the SCFF only pays districts for awarded certificates that require at least 16, I restrict certificates to awards that meet this credit threshold. The degree file tracks awarded certificates for various ranges of required units which allows me to make this restriction.

College-Level Student Covariates

I generate student covariates at the college level (e.g., average age, racial composition) using a restricted sample of students who are enrolled in at least one credit-bearing course in a given sampled academic year. This restriction allows me to capture student characteristics among a group that is more likely to pursue a degree since the administrative data also capture students who enroll in non-credit courses.

Summary Statistics

Table 3 presents summary statistics for the full college sample (i.e., the number that corresponds to the counts in Table 2) in the 2017-18 baseline year. I choose this year as the baseline because it was the final year preceding the SCFF's implementation. Since the college samples for each degree type are nearly identical (the ADT sample excludes a single college that is included in the certificate and associate degree samples in this year), I show statistics for the associate degree and certificate college sample only. In this sample, the average college awards 2.9 certificates, 4.7 associate degrees, and 2.0 ADTs per 100 enrolled students. Note that I do not include ADTs in associate degree counts here and for the remainder of the paper.

Table 3.3. Summary Statistics for All Colleges

Variable	
<u>Outcomes</u>	
Certificates per 100 Students	2.86
	(2.04)
Associate Degrees per 100 Students	4.72
	(2.19)
ADTs per 100 Students	2.03
	(1.01)
<u>Covariates</u>	
Total Student Enrollment (in Thousands)	21.42
	(12.92)
Units Attempted in an Academic Year	11.50
	(2.36)
Age	27.19
	(2.99)
Proportion Female	0.54
	(0.07)
Proportion Hispanic	0.44
	(0.16)
Proportion White	0.28
	(0.14)
Proportion Asian	0.10
	(0.09)
Proportion Black	0.07
	(0.06)
Proportion Promise Grant Recipients	0.45
	(0.13)
Proportion Pell Grant Recipients	0.19
	(0.08)
Number of Colleges	114

Notes: Standard deviations displayed in parentheses. Each observation represents a college in the 2017-18 baseline academic year. Degree counts per 100 students use a college's total awareded degrees and number of enrolled students in the baseline year. ADTs are not included in associate degree counts. Certificate counts include awards that require 16 or more units. Covariates represent average student characteristics among students enrolled in at least one credit-bearing course.

Methods

I employ a series of models to estimate the SCFF's effect on the production of certificates, associate degrees, and ADTs. Unbiased estimates of the SCFF's effects on certificate and degree production could most credibly be obtained if a subset of CCC colleges had been randomly assigned to "treatment" by the SCFF while the remaining colleges had remained funded by the prior enrollment-based formula. Then, I could estimate an effect as the difference in outcome across treatment and control groups. Of course, these conditions were not present in the SCFF's implementation and thus, this ideal research design is unavailable for use.

Alternatively, an available but naïve design is an Ordinary Least Squares (OLS) model which compares changes in a college outcome pre- and post-SCFF. Consider the following model

$$(1)\ Y_{it} = \beta_1 SCFF_t + \beta_2 \alpha_i + e_{it}$$

where Y_{it} represents the number of certificates, associate degrees, or ADTs granted by college i in year t, $SCFF_t$ is a binary indicator which equals 1 if the SCFF was operational in year t and 0 otherwise, and α_i represents college fixed effects which capture time-invariant heterogeneities across colleges. The SCFF's effect is captured by $\hat{\beta}_1$. However, this OLS estimator may be biased if it captures awarding trends that are contemporaneous but unrelated to the policy.

Interrupted Time Series

To improve upon identification, I use an ITS design to estimate the effects of the SCFF on systemwide certificate and degree production. This model takes the following form

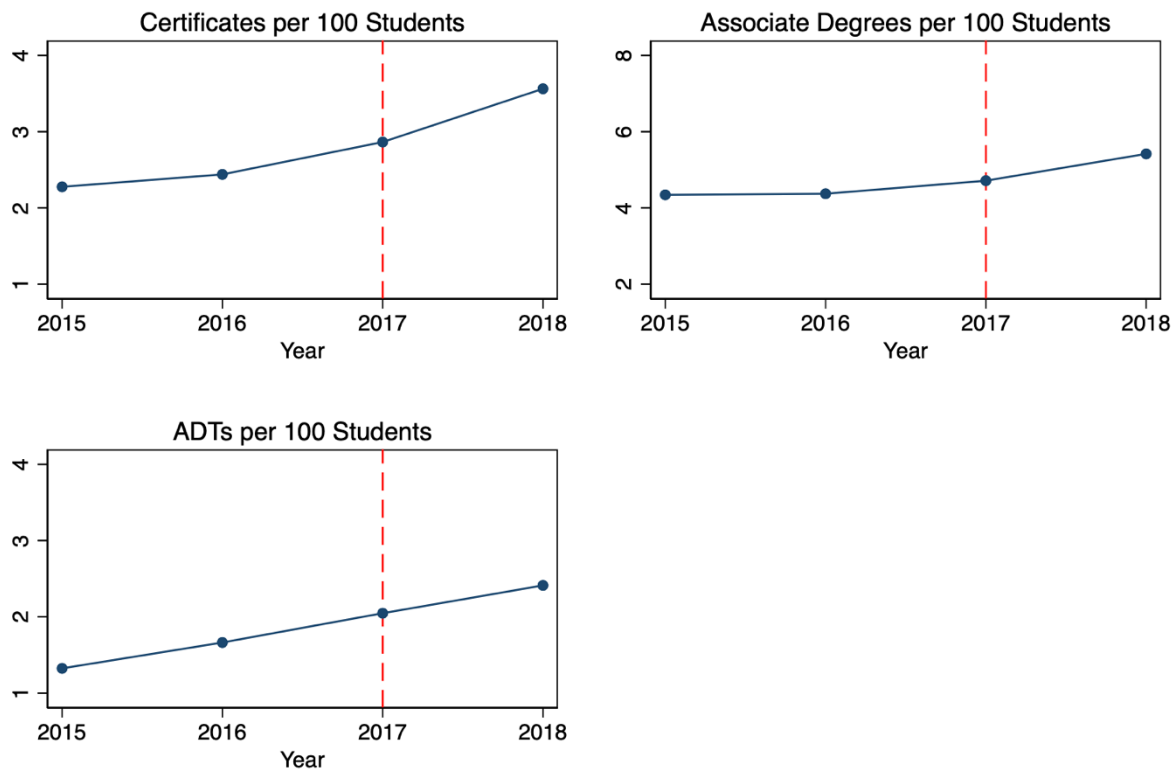
$$(2)\ Y_{it} = \beta_1 Year_t + \beta_2 SCFF_t + \beta_3 X_{it} + \beta_4 \alpha_i + e_{it}$$

where $Year_t$ equals the number of years passed since the start of the observational period. There are four total years where the first year denotes the 2015-16 academic year and the fourth year denotes the 2018-19 academic year which is the SCFF's first operational year. X_{it} is a vector of time-varying college characteristics. In each analytical model described in this section, I include college controls for logged total enrollment, student composition by race and gender, as well as average student age and number of enrolled units in a given academic year. Since there is only a single year of post-SCFF data available for use, I omit the conventional ITS term that captures the number of years following an intervention. Each other variable is defined as before.

$\hat{\beta}_1$ nets out the linear trend in an outcome in the pre-SCFF period. $\hat{\beta}_2$ captures the SCFF's effect on an outcome, net of the changes expected due to the time trend and covariates. In each paper model, I use standard errors clustered at the college level to account for non-independence between college-years. ITS results are displayed in Table 6 below. Estimated policy effects are valid if the pre-SCFF trend estimated by $\hat{\beta}_1$ would have continued in the post-SCFF period had the policy not been implemented. This assumption is untestable since I cannot observe counterfactual college outcomes.

Figure 1 presents the mean number of awarded certificates, associate degrees, and ADTs per 100 enrolled students across systemwide colleges in the analytical period. Prior to the SCFF's adoption, there was a sharp rise in certificate and degree production across the CCC system. On average, certificates, associate degrees, and ADTs increased by 21.1 percent, 8.5 percent, and 54.0 percent in just three years. This trend is part of longer-running increase in certificate and degree production seen in Figure A1. In the SCFF's first operational year, certificate and associate degree production grew at a faster pace than in prior years whereas ADT production appears unaffected.

Figure 3.1. Trends in Mean Awarding Outcomes



Notes: Each point displays a mean college outcome per 100 enrolled students. Year denotes the fall year of a given academic year. The vertical line displays the final year before the SCFF's implementation in 2017-18.

Comparative Interrupted Time Series

I also use a CITS framework to estimate the SCFF's effects on certificate and degree production. In it, I compare effects across college groups that ought to have been more or less financially affected by the policy in order to "difference out" time-varying confounds which may bias the ITS. For this reason, I consider the CITS to be a stronger analytical technique than the ITS. However, the policy effects estimated by the ITS and CITS take on different interpretations. The ITS can only estimate the total effect of the SCFF since it does not use a college control group. This includes the effect of the state's emphasis on college completion, which all colleges may have experienced, and the effect of the SCFF's degree incentives, which some colleges may have experienced more than others. Conversely, the CITS is able to estimate the specific effect of the SCFF's degree incentives with the use of a college control group that is less affected by this aspect of the policy.

I use two distinct college grouping methods, described below, to estimate the following CITS model

(3) $Y_{it} = \beta_1 Year_t + \beta_2 SCFF_t + \beta_3 Year_t \cdot Treat_i + \beta_4 SCFF_t \cdot Treat_i + \beta_5 X_{it} + \beta_6 \alpha_i + e_{it}$

where $Treat_i$ equals 1 if college *i* is ostensibly more affected by the policy and 0 otherwise. Each other variable is defined as before. $\hat{\beta}_1$ and $\hat{\beta}_3$ net out time-varying differences in a given outcome that are measured in the pre-SCFF period. These differences are estimated separately for each group. I measure the SCFF's total effect on more-affected colleges as $\hat{\beta}_2 + \hat{\beta}_4$ and the total effect on less-affected colleges as $\hat{\beta}_2$. Note that these group-specific estimates are analogous to ITS estimates in that they do not use a control group. Thus, the identifying assumption of continuity in the pre-SCFF awarding trends similarly applies to these estimates.

I measure the "net effect" of SCFF incentives as the effect on more-affected colleges less the effect on less-affected colleges, or $\hat{\beta}_4$. This estimate is valid if $\hat{\beta}_1$ and $\hat{\beta}_3$ are properly estimated such that there are not remaining time-varying differences across college groups that are related to awarding outcomes (Dee & Jacob, 2011; Hallberg et al., 2018). This assumption is again untestable because I cannot observe counterfactual college outcomes. However, I look for suggestive evidence that this assumption is satisfied by comparing mean degree awarding trends across each set of CITS college groups in the analytical period. If pre-SCFF degree trends exhibit linear patterns, this implies that linear CITS model specified in Equation (3) is a good fit for the data. In turn, this suggests that the model properly accounts for counterfactual outcomes for each college group. I present this set of results for each grouping method below after describing the manner in which I construct each group.

Grouping by Community Supported (CS) Status

The majority of CCC colleges receive state apportionment funds. Thus, the SCFF's degree incentives affect the revenue of most colleges. However, 12 CS colleges do not receive state apportionment revenue because they raise high levels of revenue from local taxes. These colleges ought to have experienced no change in financial incentives from the SCFF because they do not rely on revenue from degree incentives regardless of how their awarding behavior changes in response to the policy. I use CS status as the first method of grouping colleges according to their treatment to the SCFF's financial incentives. I denote non-CS colleges as "financially-affected" and CS colleges as "financially-unaffected".

For a detailed description of CS status and discussion of the how the SCFF differentially affected the financial incentives of CS and non-CS colleges, see *Paper 2: Impact of Financial Aid Incentives on Student Receipt in the California Community College System.*

Summary Statistics by College CS Status

Table 4 presents summary statistics across CS and non-CS college groups in the 2017-18 baseline year. I again show statistics for the sample used for certificates and associate degrees. Non-CS colleges award roughly 0.6 fewer certificates and 1.5 more associate degrees per 100 enrolled students than CS colleges, on average. Each group awards ADTs at a very similar rate. Non-CS colleges tend to enroll a larger number of students who are younger, more likely to be Hispanic or Black, and less likely to be White or Asian. Finally, students attending non-CS colleges are more likely to be recipients of the Promise or Pell Grant. This is expected because non-CS colleges are located in state regions with relatively weaker tax bases. Students attending these college are thus lower-income, on average, and are more likely to use financial aid programs. By including college-level controls for student characteristics and college fixed effects in the CITS model, I attempt to net out variation in degree awarding that is related to these differences.

Table 3.4. Summary Statistics by College CS Status

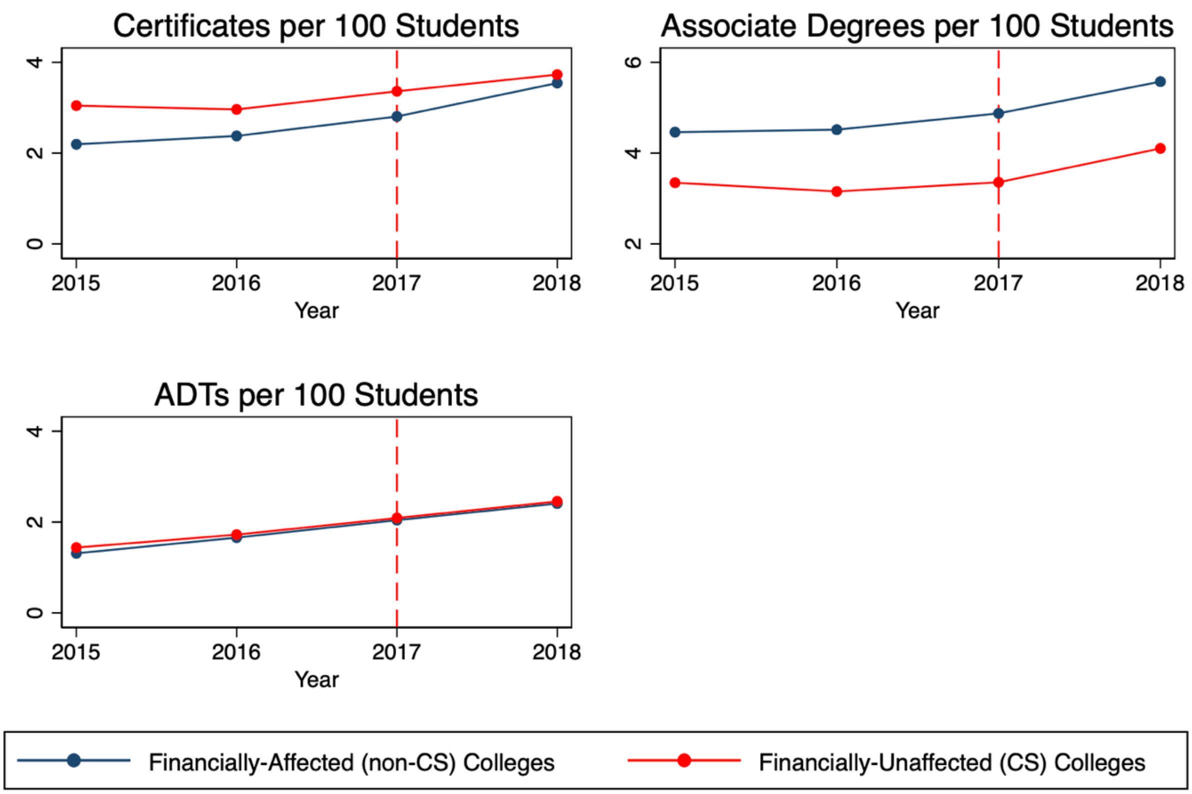
Variable	Non-CS Colleges	CS Colleges
<u>Outcomes</u>		
Certificates per 100 Students	2.81	3.36
	(2.05)	(1.94)
Associate Degrees per 100 Students	4.87	3.36
	(2.23)	(1.07)
ADTs per 100 Students	2.02	2.09
	(1.04)	(0.64)
<u>Covariates</u>		
Total Student Enrollment (in Thousands)	21.89	17.45
	(13.25)	(9.05)
Units Attempted in Academic Year	11.62	10.48
	(2.42)	(1.50)
Age	26.97	29.12
	(2.84)	(3.69)
Proportion Female	0.54	0.56
	(0.07)	(0.03)
Proportion Hispanic	0.46	0.33
	(0.16)	(0.08)
Proportion White	0.28	0.30
	(0.15)	(0.14)
Proportion Asian	0.09	0.19
	(0.08)	(0.11)
Proportion Black	0.07	0.03
	(0.06)	(0.01)
Proportion Promise Grant Recipients	0.47	0.33
	(0.12)	(0.09)
Proportion Pell Grant Recipients	0.19	0.11
	(0.08)	(0.04)
Number of Colleges	102	12

Notes: Standard deviations displayed in parentheses. Each observation represents a college in the 2017-18 baseline academic year. Degree counts per 100 students use a college's total awareded degrees and number of enrolled students in the baseline year. Certificate counts include awards that require at least 16 units. ADTs are not included in associate degree counts. Covariates represent average student characteristics among students enrolled in at least one credit-bearing course.

College Awarding Trends by CS Status

Figure 2 presents mean awarding trends by CS status. Prior to the SCFF, each outcome exhibits comparable gains across college groups. Each outcome also exhibits a stable, linear trend in the pre-SCFF period. This suggests that the linear fit imposed by the CITS model is appropriate. It also supports the identifying assumption that there is not uncontrolled variation in awarding outcomes that differentially affects college groups. These trends also preview that non-CS colleges appear to make increased gains in certificate awarding but not associate degree or ADT awarding relative to CS colleges.

Figure 3.2. Trends in Mean Awarding Outcomes by CS Status



Notes: Each point displays a mean college outcome per 100 enrolled students. Year denotes the fall year of a given academic year. The vertical line displays the final year before the SCFF's implementation in 2017-18.

Grouping by Baseline Pell Receipt Rate

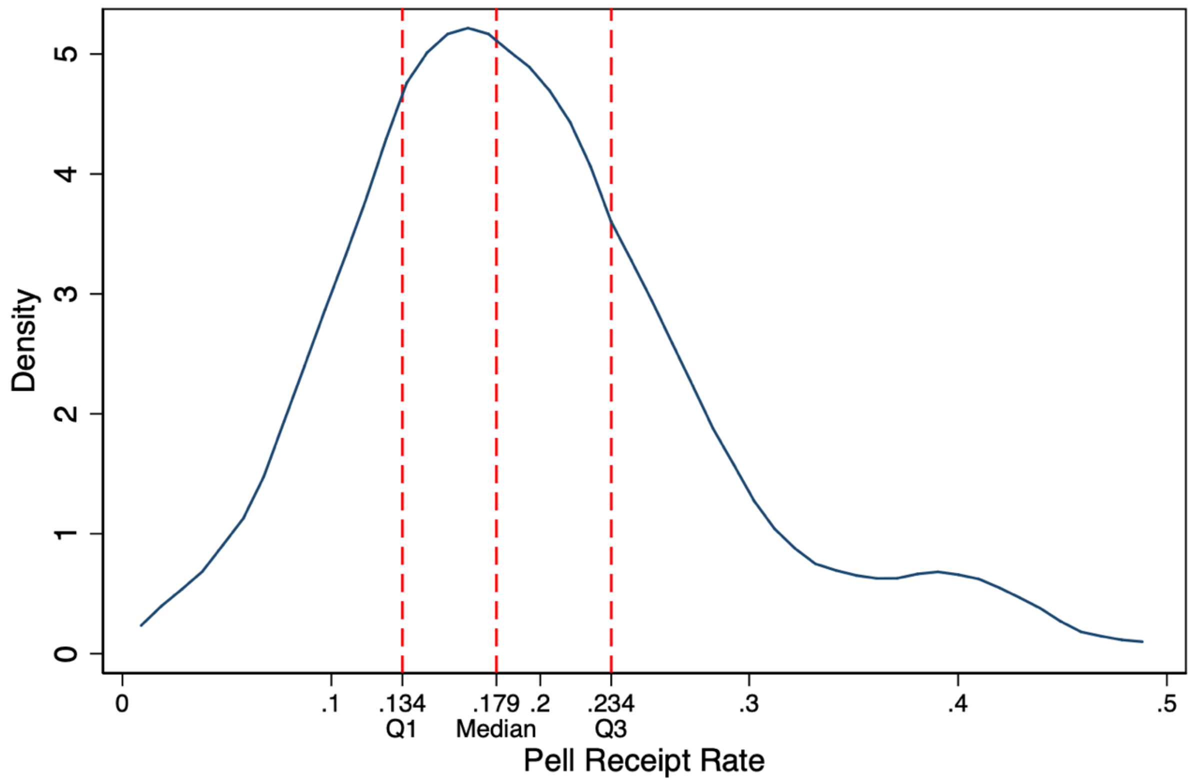
In the second CITS grouping method used to estimate Equation (3), I again compare colleges that face higher and lower degree incentives by using a college's proportion of students who are financial aid recipients. A college with a higher proportion of aid recipients faces higher incentives for degree awarding because the SCFF pays a higher rate for degrees awarded to Pell and Promise Grant recipients than for those awarded to non-recipients, seen in Table 1 above.

While the purpose of the CS grouping method is to compare colleges with some financial incentives to colleges with no financial incentives, the purpose of the present method is to compare colleges with high financial incentives to colleges with low financial incentives. I view each of these comparisons as providing useful information regarding the efficacy of the SCFF's financial incentives. Accordingly, I drop CS colleges from the present CITS model so this group of colleges without financial incentives does not appear in the group that is meant to have low financial incentives. This also ought to make the results of each model less interdependent since the less-affected group in each model will not consist of a similar group of colleges.

I use a college's proportion of students who are Pell recipients in the 2017-18 baseline year to assign group status. I use this year as a baseline since it preceded the SCFF's implementation. I choose this measure as opposed to some combination of Pell and Promise receipt because a college's Pell and Promise receipt rates are highly correlated. Almost every CCC student who receives a Pell Grant also receives a Promise Grant, so I do not expect that variability in a college's Promise rate will provide additional information regarding the extent to which it is affected by degree incentives.

I flag colleges that fall in the top and bottom quartile of Pell receipt among non-CS colleges. I denote these groups as "high-Pell" and "low-Pell", respectively. Figure 3 displays the distribution of Pell receipt across non-CS colleges with thresholds for the high- and low-Pell groups. In the CITS model, I compare policy effects across these groups and drop colleges that fall in the middle two quartiles. I choose this method so that the high- and low-Pell groups do not consist of colleges with relatively similar baseline Pell receipt rates.

Figure 3.3. Distribution of Baseline Pell Receipt Rate with Quartiles



Notes: Figure displays the distribution Pell receipt rate in the 2017-18 baseline year for 102 sampled non-CS colleges. In my CITS model, I flag colleges that have lower receipt than the first quartile (Q1) threshold as low-Pell. I flag colleges that have higher receipt than the third quartile (Q3 threshold as high-Pell.

Summary Statistics for High and Low-Pell College Groups

Table 5 presents summary statistics for high- and low-Pell college groups. High-Pell colleges award roughly .7 more certificates, 2.1 more associate degrees, and .9 more ADTs per enrolled 100 students than low-Pell colleges, on average. Students attending high-Pell colleges enroll in more units and are younger than students attending low-Pell colleges, on average. They are more likely to be Hispanic and less likely to be White or Asian. Finally, there are large baseline differences in financial aid receipt among college groups. Students attending high-Pell colleges are 22 percentage points more likely to receive a Promise Grant and 25 percentage points more likely to receive a Pell Grant.

This confirms that high-Pell colleges face higher financial incentives since they can earn higher revenue from the SCFF's premium rates by awarding degrees to financial aid recipients.

Table 3.5. Summary Statistics for High- and Low-Pell College Groups

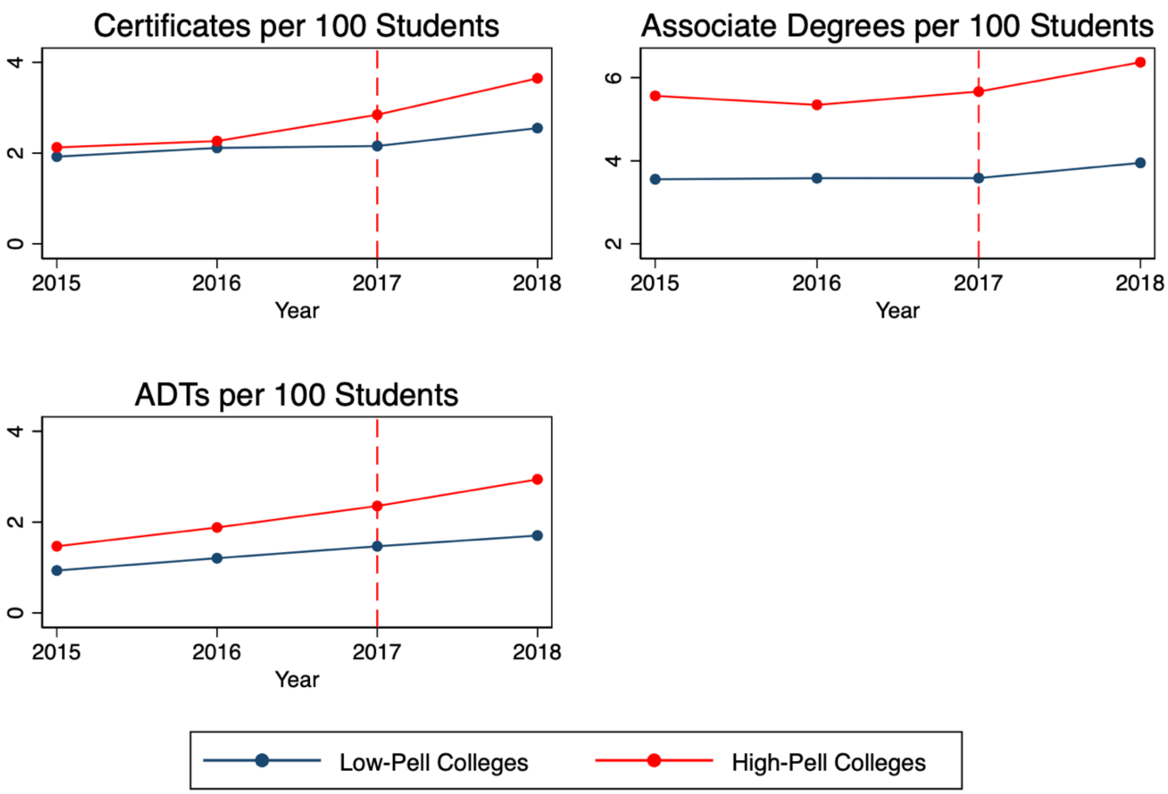
Variable	High-Pell Colleges	Low-Pell Colleges
Outcomes		
Certificates per 100 Students	2.84	2.16
	(1.84)	(1.31)
Associate Degrees per 100 Students	5.67	3.58
	(2.07)	(1.43)
ADTs per 100 Students	2.35	1.47
	(0.76)	(0.89)
Covariates		
Total Student Enrollment (in Thousands)	19.98	21.89
	(10.75)	(15.20)
Units Attempted in Academic Year	13.26	10.43
	(1.37)	(3.35)
Age	25.70	29.27
	(1.30)	(3.58)
Proportion Female	0.57	0.48
	(0.03)	(0.11)
Proportion Hispanic	0.54	0.36
	(0.17)	(0.12)
Proportion White	0.25	0.31
	(0.15)	(0.10)
Proportion Asian	0.05	0.13
	(0.04)	(0.11)
Proportion Black	0.06	0.08
	(0.05)	(0.07)
Proportion Promise Grant Recipients	0.58	0.36
	(0.07)	(0.12)
Proportion Pell Grant Recipients	0.31	0.10
	(0.06)	(0.03)
Number of Colleges	26	26

Notes: Standard deviations displayed in parentheses. Each observation represents a college in the 2017-18 baseline academic year. Degree counts per 100 students use a college's total awareded degrees and number of enrolled students in the baseline year. Certificate counts include awards that require at least 16 units. ADTs are not included in associate degree counts. Covariates represent average student characteristics among students enrolled in at least one credit-bearing course.

College Awarding Trends across High- and Low-Pell Colleges

Figure 4 presents mean awarding trends across high- and low-Pell colleges. Prior to the SCFF, certificate awarding increased among high-Pell colleges while stagnating among low-Pell colleges. Trends in associate awarding were similarly stagnant across college groups and trends in ADT awarding were similarly increasing across college groups. Each outcome exhibits a stable, linear trend in the pre-SCFF period. This suggests that the linear fit imposed by the CITS model is appropriate for this grouping method too. It also supports the identifying assumption that there is not variation in awarding outcomes which differentially affect college groups. Finally, there do not appear to be substantial differences in post-SCFF awarding gains across high- and low-Pell groups. While high-Pell colleges appear to make larger gains in certificates, they also exhibit a slightly higher pre-SCFF trend. This makes the size and significance of the corresponding CITS effect ambiguous.

Figure 3.4. Trends in Mean Awarding Outcomes by CS Status



Notes: Each point displays a mean college outcome per 100 enrolled students. Year denotes the fall year of a given academic year. The vertical line displays the final year before the SCFF's implementation in 2017-18.

Main Estimation Results

This section presents ITS and CITS model results in which certificate, associate degree, and ADT outcomes are measured in terms of the number of degrees that a college awards per 100 enrolled students in a given year. In Appendix B, I present the same set of models in which the same credentials are measured as the logged number of awards in a given year. In certain models and outcomes, there are non-negligible differences in the magnitude and significance of estimated policy effects. However, they do not substantially change my conclusions regarding the SCFF's effects on certificate and degree production. I discuss differences between the two sets of results in Appendix B.

ITS Estimates of Systemwide Effects

Table 6 presents ITS estimates from Equation (2). This model evaluates the SCFF's homogenous effects on awarding outcomes across the full sample of CCC colleges. I find that the SCFF was associated with an increase of 0.4 certificates per 100 enrolled students in its first operational year. This represents a 12.7 percent increase relative to the mean certificate awarding rate in the 2017-18 baseline year which preceded the SCFF's implementation. The policy was also associated with a 0.5 increase in associate degrees per 100 enrolled students which represents 10.7 percent of the baseline mean associate awarding rate. However, this effect was only marginally significant. Finally, the policy was associated with a null change in ADT awarding that was small in magnitude.

Table 3.6. ITS Results for Systemwide Effects

Variable	Certificates per 100 Students	Associate Degrees per 100 Students	ADTs per 100 Students
$SCFF_t$	0.364**	0.504*	-0.022
	(0.146)	(0.257)	(0.039)
$Year_t$	0.350***	0.266***	0.414***
	(0.081)	(0.078)	(0.028)
Mean of Y in Baseline Year	2.864	4.715	2.030
Sample Size	454	456	450
Number of Colleges	114	114	113

Notes: Each model includes controls for a college's logged total enrollment, student composition by race and gender, average student units enrolled in an academic year, and college fixed effects. Standard errors shown in parentheses are clustered at the college level. Baseline year statistics are computed for the 2017-18 academic year which preceded the SCFF. ***p<0.01, **p<0.05, *p<0.10.

Estimates of Heterogeneous Effects by CS Status

Table 7 presents results from the CITS model, estimated by Equation (3), that compares colleges that were financially affected (non-CS colleges) or unaffected (CS colleges) by degree incentives. In addition to the primary CITS coefficients, it reports group-specific effects for each college group. The group-specific effect is equal to the estimated $SCFF_t$ coefficient for CS colleges and the sum of the estimated $SCFF_t$ and $SCFF_t \cdot Treat_i$ coefficients for non-CS colleges. Finally, the net effect, which equals the difference between these two group-specific effects, is captured by the estimated $SCFF_t \cdot Treat_i$ coefficient. I interpret this as the specific effect of the SCFF's financial incentives. If degree incentives were the catalyst for awarding gains, as opposed to the state's emphasis for degree completion which was lower-stakes and may have affected all colleges similarly, I expect this net effect to be positive and large.

Table 3.7. CITS Results with Financially-Affected (non-CS) and Financially-Unaffected (CS) College Groups

Variable	Certificates per 100 Students	Associate Degrees per 100 Students	ADTs per 100 Students
$SCFF_t$	0.009	0.773***	0.045
	(0.328)	(0.245)	(0.076)
$SCFF_t$ x $Treat_s$	0.398	-0.298	-0.073
	(0.364)	(0.398)	(0.086)
$Year_t$	0.390**	0.108	0.340***
	(0.150)	(0.107)	(0.059)
$Year_t$ x $Treat_s$	-0.045	0.179	0.083
	(0.141)	(0.114)	(0.059)
Effect on Financially-Affected (non-CS) Colleges	0.407**	0.475	-0.029
	(.159)	(.290)	(0.043)
Effect on Financially-Unaffected (CS) Colleges	0.009	0.773***	0.045
	(0.328)	(0.245)	(0.076)
Mean of Y in Baseline Year among Financially-Affected (non-CS) Colleges	2.806	4.875	2.023
Sample Size	454	456	450
Number of Colleges	114	114	113

Notes: Each model includes controls for a college's logged total enrollment, student composition by race and gender, average student units enrolled in an academic year, and college fixed effects. Standard errors shown in parentheses are clustered at the college level. Baseline year statistics are computed for the 2017-18 academic year which preceded the SCFF. ***p<0.01, **p<0.05, *p<0.10.

The SCFF was associated with a larger increase in certificate awarding among non-CS colleges than CS colleges in its first operational year. Non-CS colleges exhibited an increase of 0.4 certificates per 100 enrolled students. By contrast, this effect among CS colleges was statistically non-significant and small in magnitude. Conversely, the policy was associated with a larger increase in associate degree awarding among CS colleges than non-CS colleges. CS colleges exhibited an increase of 0.8 associate degrees per 100 enrolled students. Non-CS colleges exhibited a smaller increase of 0.5 associate degrees per 100 students that was statistically non-significant. Finally, ADT awarding exhibited a null effect that was small in magnitude across each college group.

For each degree outcome, the net effect of financial incentives is null. However, for certificates and associate degrees, these effects show a substantial magnitude, albeit with mixed signs. Non-CS colleges made gains in certificate awarding that exceeded those made by CS colleges by a margin of 0.4 certificates per 100 enrolled students. Conversely, CS colleges made gains in associate degree awarding that exceeded those made by non-CS colleges by a margin 0.3 associate degrees per 100 enrolled students.

While the positive net effect in the certificate model does provide some evidence that degree incentives were efficacious, the negative net effect in the associate degree model cautions against this interpretation. These results may instead suggest that non-CS colleges responded to degree incentives by shifting focus from associate degree awarding to certificate awarding. While prior research on PF policies finds evidence for this type of tradeoff between shorter- and longer-run student outcomes (Hillman et al., 2014, 2018; Li & Kennedy, 2018), I am hesitant to make this conclusion with only a single year of post-SCFF data.

The lack of statistical significance in the net effect coefficients appears to result from limited statistical power in this model. The standard error of 0.4 for the net effect in both the certificate and associate degree models implies that a coefficient smaller than 0.8 would not reach statistical significance at the 0.05 level[90]. An effect of this size would

[90] This is an approximation using a t-statistic of 2.

represent 29 percent of the mean certificate awarding rate and 16 percent of the mean associate degree awarding rate among non-CS colleges in the 2017-18 baseline year. Thus, this CITS model would only detect significant net effects under quite large differences across college groups.

Estimates of Heterogeneous Effects across High- and Low-Pell Colleges

Finally, Table 8 presents CITS results, estimated by Equation (3), for colleges groups with higher and lower baseline Pell receipt rates. Groups are comprised of non-CS colleges in the top and bottom quartile of this measure, respectively, in the 2017-18 baseline year. A high-Pell college ought to earn higher incentives for its awarded degrees than a low-Pell college, on average, because the SCFF pays a premium rate for degrees awarded to financial aid recipients and aid recipients make up a larger share of the student population in a high-Pell college.

Like the previous table, this table reports primary CITS coefficients and group-specific effects. The group-specific effect is equal to the estimated $SCFF_t$ coefficient for low-Pell colleges and the sum of the estimated $SCFF_t$ and $SCFF_t \cdot Treat_i$ coefficients for high-Pell colleges. Finally, the net effect, which equals the difference between these two group-specific effects, is captured by the estimated $SCFF_t \cdot Treat_i$ coefficient. As before, I expect this net effect to be positive and large if degree incentives drove reforms in college awarding behavior.

Table 3.8. CITS Results with High- and Low-Pell Groups

Variable	Certificates per 100 Students	Associate Degrees per 100 Students	ADTs per 100 Students
$SCFF_t$	0.296*	0.224*	-0.033
	(0.167)	(0.126)	(0.067)
$SCFF_t$ x $Treat_s$	0.212	0.480	0.131
	(0.277)	(0.316)	(0.119)
$Year_t$	0.144	0.181	0.296***
	(0.099)	(0.114)	(0.048)
$Year_t$ x $Treat_s$	0.265*	-0.012	0.200***
	(0.145)	(0.110)	(0.059)
Effect on High-Pell Colleges	0.508**	0.704***	0.098
	(0.222)	(0.257)	(0.109)
Effect on Low-Pell Colleges	0.296*	0.224*	-0.033
	(0.167)	(0.126)	(0.067)
Mean of Y in Baseline Year among High-Pell Colleges	2.845	5.667	2.353
Sample Size	207	208	206
Number of Colleges	52	52	52

Notes: Each model includes controls for a college's logged total enrollment, student composition by race and gender, average student units enrolled in an academic year, and college fixed effects. Standard errors shown in parentheses are clustered at the college level. Baseline year statistics are computed for the 2017-18 academic year which preceded the SCFF. ***p<0.01, **p<0.05, *p<0.10.

I find that the SCFF was associated with an increase in certificate and associate degree awarding among both groups in its first operational year. These effects were marginally significant-to-significant. Certificate awarding increased by 0.5 and 0.3 certificates per 100 enrolled students among high- and low-Pell groups, respectively. Associate degree awarding increased by 0.7 and 0.2 associate degrees per 100 enrolled students among high- and low-Pell groups, respectively. ADTs exhibited a null effect that was small in magnitude for each college group.

The net effect for each outcome is positive and substantial in size but statistically non-significant. This suggests that degree incentives prompted high-Pell colleges to make increased awarding gains relative to low-Pell colleges. The standard errors for this coefficient across outcomes are slightly smaller than those of the previous CITS model. Still, they reveal that there is limited power in this model to detect significant differential awarding effects.

Discussion

I find evidence that the SCFF increased certificate and degree production in the CCC system in its first operational year. The policy was associated with a 12.7 percent increase in awarded certificates per 100 enrolled students and a 10.7 percent increase in awarded associate degrees per 100 enrolled students. However, the policy was associated with a small, null change in ADT awarding.

I find some evidence that heterogeneity in degree awarding effects across colleges was driven by the SCFF's financial incentives. I use a CITS model to compare awarding changes across college groups that were financially affected or unaffected by financial incentives, as determined by their CS status. This model reports that financially-affected colleges increased certificate awarding by a greater margin but increased associate awarding by a smaller margin relative to financially-unaffected colleges. Neither of these differences are statistically significant.

I also use a second CITS model to compare colleges with higher and lower baseline proportions of Pell recipients. High-Pell colleges faces higher financial incentives than low-Pell colleges because the SCFF pays premium rates for degrees awarded to financial aid recipients. This model reports that high-Pell colleges make larger gains in certificate, associate degree, and ADT awarding than low-Pell colleges. Like the previous model, these differential effects are not statistically significance. The limited statistical power in both CITS models appears to explain why these effects are null despite being moderate in size.

It is sensible that certificate awarding exhibits larger systemwide gains than associate or ADT awarding in the SCFF's first operational year. While a certificate may be completed in less than a year, associate degrees and ADTs require a minimum of two years. In practice, these longer degrees have a significantly longer average time to completion among CCC students (Foundation for California Community Colleges, 2017). Thus, in the SCFF's first operational year, colleges ought to have had a greater ability to boost certificate awarding than associate degree or ADT awarding.

Further, consider two potential policy tools a college may have used to expand certificate and degree production: automatic awarding and stackable credentials. Automatic awarding involves implementing an auditing system that automatically awards degrees to students who have met degree requirements, thereby reducing administrative barriers to degree attainment. Stackable credentials involves designing curricular pathways in which students can earn shorter-term degrees while working towards a longer-term degree (Bohn & McConville, 2018). For instance, a college could design a curriculum in energy efficiency in which a student may complete introductory coursework, after which they earn a certificate, and advanced coursework, after which they earn an associate degree.

I expect that a college that implements automatic awarding would increase production of certificates by a greater margin than associate degrees or ADTs. This is because a student who previously would not have earned a certificate, either because its requirements were unaligned with their degree goal or because they were unaware they had earned its requisite units, would be encouraged to earn one. However, I do not expect that policy would have an appreciable effect on associate or ADT awarding. Since a student must complete more units and a more laborious curriculum to attain these degrees, it is unlikely that a student would meet the requirement for either degree without attaining it. While it is less clear whether stackable credentials would boost certificates or degree awarding more in the long-run, I posit that this policy would disproportionately produce gains in certificate awarding in the SCFF's first operational year. A student who is attempting to earn an associate degree or ADT could earn a certificate in this first year but a student who is attempting to earn a certificate could not earn an associate degree or ADT in this year.

CITS results show that while the SCFF's financial incentives appear to have been a catalyst for reform, colleges that did not face financial incentives still exhibited gains in certificate and associate degree production. This suggests that the policy may have also worked by signaling the state's emphasis on degree completion. Prior qualitative research finds that there are multiple "theories of action" through which a PF policy may encourage reform (Dougherty & Reddy, 2011). In addition to changes in an institution's revenue, an institution may respond because of increased awareness of state goals. In the present policy context, this may explain why colleges that were financially unaffected by the SCFF still made gains in awarding.

Future research should evaluate the SCFF's effects on certificate and degree production beyond its first year of operation[91]. The policy effects estimated in the present analysis may be dampened for several reasons. First, the SCFF's hold harmless provision was operational in this first year. That is, a college could gain but not lose

[91] However, the onset of Covid-19 may preclude time-series analyses in future years.

revenue as a result of awarding changes. In turn, college administrators may have felt less urgency to implement reforms because of they did not face the risk an immediate revenue decline. Second, the SCFF's rollout was rapid. College administrators did not have time to respond to degree incentives before the policy was implemented and their responses were likely limited in the first policy year. Third, associate degrees and ADTs require a minimum of two years to complete. Thus, the SCFF may affect production of these degrees in a lagged manner.

Conclusion

I find that the SCFF increased certificate and associate degree awarding in the CCC system by roughly 13 and 11 percent per 100 enrolled students, respectively, in its first operational year. However, the policy was associated with a small, null change in ADT awarding.

I also find some evidence that the SCFF's financial incentives were a driver of increased certificate and degree production. Colleges that faced higher financial incentives made increased awarding gains relative to colleges that faced lower financial incentives for most credential outcomes across two distinct grouping methods. However, these differences were not statistically significant. Moreover, colleges that did not face financial incentives nonetheless made gains in certificate and degree production. Thus, the SCFF worked both through its financial incentives and by signaling the state's increased emphasis on degree completion across the CCC system.

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Appendix A: Regression Results with Logged Degree Counts

I use this section to present the main-text models using degree outcomes that are measured in logged terms as opposed to counts per 100 enrolled students. I find that there may be differences in the two sets of results, depending on the model and outcome. In each model, I interpret each coefficient, β_i, as a percent effect by applying the transformation $exp(\beta_i) - 1$.

Table B1 presents ITS estimates from Equation (2). I find that in the SCFF's first operational year, the policy was associated with a 12.5 percent increase in certificates, compared to 12.7 reported in the main-text model. Associate awarding increased by 7.0 percent, compared to 10.7 percent reported in the main-text model. ADT awarding decreased by 7.8 percent, compared to an increase of 1.1 percent decrease in the main-text model. Of the three effects, there is only a substantial difference in magnitude between model estimates in ADT awarding. Further, while the main model reports an ADT effect that does not approach statistical significance, the model in the present section reports a significant effect.

Table 3.A1. ITS Results for Systemwide Effects: Logged Results

Variable	Logged Certificates	Logged Associate Degrees	Logged ADTs
$SCFF_t$	0.118**	0.068***	-0.081***
	(0.052)	(0.025)	(0.028)
$Year_t$	0.119***	0.051***	0.259***
	(0.029)	(0.012)	(0.020)
Sample Size	454	456	450
Number of Colleges	114	114	113

Notes: Each model includes controls for a college's logged total enrollment, student composition by race and gender, average student units enrolled in an academic year, and college fixed effects. Standard errors shown in parentheses are clustered at the college level. ***p<0.01, **p<0.05, *p<0.10.

Table B2 presents CITS results, estimated by Equation (3), that compare colleges that were financially affected (non-CS colleges) or unaffected (CS colleges) by degree incentives. I compare only the net effect, which estimates difference in the non-CS group effect less the CS group effect, between this model and the main-text model. The net effect for certificate awarding is a 23.8 percent increase, compared to the 14.2 percent increase reported in the main model. For associate degree awarding it is a 12.1 percent decrease, compared to the 6.1 percent decrease reported in the main model. For ADT awarding, it is a 9.0 percent decrease, compared to the 3.3 percent decrease reported in the main model.

Table 3.A2. CITS Results with Financially-Affected and Financially-Unaffected College Groups: Logged Results

Variable	Logged Certificates	Logged Associate Degrees	Logged ADTs
$SCFF_t$	-0.073	0.184***	0.005
	(0.115)	(0.048)	(0.044)
$SCFF_t$ x $Treat_s$	0.213*	-0.129**	-0.094*
	(0.123)	(0.056)	(0.053)
$Year_t$	0.160**	0.019	0.164***
	(0.075)	(0.028)	(0.032)
$Year_t$ x $Treat_s$	-0.046	0.036	0.107***
	(0.075)	(0.030)	(0.037)
Effect on Financially-Affected (non-CS) Colleges	0.140** (0.056)	0.054** (0.027)	-0.089*** (0.030)
Effect on Financially-Unaffected (CS) Colleges	-0.073 (0.115)	0.184*** (0.048)	0.005 (0.044)
Sample Size	454	456	450
Number of Colleges	114	114	113

Notes: Each model includes controls for a college's logged total enrollment, student composition by race and gender, average student units enrolled in an academic year, and college fixed effects. Standard errors shown in parentheses are clustered at the college level. ***p<0.01, **p<0.05, *p<0.10.

The logged models presented here estimate substantially larger differences in awarding changes across groups than the main models. Further, the logged models report marginally significant-to-significant net effects across degree outcomes whereas the main models report only null effects.

Table B3 presents CITS results, estimated by Equation (3), that compare colleges with a higher or lower proportion of Pell recipients in the 2017-18 baseline year. I again compare only the net effect, which estimates difference in the high-Pell group effect less the low-Pell group effect, between this model and the main-text model. The net effect for certificate awarding is a 1.2 percent increase, compared to the 7.5 percent increase reported in the main model. For associate awarding, it is a 6.5 percent increase, compared to the 8.5 percent increase reported in the main model. For ADT awarding, it is a 6.6 percent decrease, compared to the 5.6 percent decrease reported in the main model. Only the certificate awarding net effect is substantially different in magnitude between these two models. Further, each net effect is not statistically significant across each models.

Table 3.A3. CITS Results with High- and Low-Pell Groups: Logged Results

Variable	Logged Certificates	Logged Associate Degrees	Logged ADTs
$SCFF_t$	0.161*	0.056*	-0.028
	(0.083)	(0.033)	(0.071)
$SCFF_t$ x $Treat_s$	0.012	0.063	-0.068
	(0.139)	(0.058)	(0.089)
$Year_t$	0.058	0.038	0.248***
	(0.047)	(0.027)	(0.035)
$Year_t$ x $Treat_s$	0.116**	-0.007	0.039
	(0.053)	(0.024)	(0.047)
Effect on High-Pell Colleges	0.173	0.119**	-0.096*
	(0.112)	(0.050)	(0.056)
Effect on Low-Pell Colleges	0.161*	0.056*	-0.028
	(0.083)	(0.033)	(0.071)
Sample Size	207	208	206
Number of Colleges	52	52	52

Notes: Each model includes controls for a college's logged total enrollment, student composition by race and gender, average student units enrolled in an academic year, and college fixed effects. Standard errors shown in parentheses are clustered at the college level. ***p<0.01, **p<0.05, *p<0.10.

This set of results indicates that the SCFF was associated with an increased trade-off between shorter- and longer-run student outcomes relative to the main-text results.

The negative ADT effect reported by the ITS is larger in magnitude which may indicate that colleges are placing less emphasis on this degree offering. The CITS model that uses CS groups reports a larger positive effect for certificate awarding and a larger negative effect for associate degree and ADT awarding. This could similarly indicate financially-affected colleges are shifting from awarding long degrees to short degrees relative to financially-unaffected colleges.

However, I am hesitant to conclude that colleges responded to the SCFF by "gaming the system" by shifting resources to increase awarding of short degrees. Notice that financially-affected colleges still exhibit an increase in associate degree awarding as a result of the SCFF, seen in the group-specific effect in Table B2. This suggests that the decline in ADT awarding systemwide and among financially-affected colleges may not be a result of the SCFF.

In sum, the results presented in the section do not substantially change my conclusions regarding the SCFF's effects on certificate and degree production. I still conclude that the SCFF increased certificate and associate degree production systemwide. Further, I still find little evidence that the SCFF's financial incentives were a catalyst for reform in college awarding.