Using Latent Profile Analysis to Derive a

Classification of Four-Year Colleges and Universities

by

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ABSTRACT

Organizational classifications are critical to a wide variety of stakeholders. Within the domain of higher education, researchers use established classifications for sample selection or within empirical models to account for unobserved organizational characteristics. Colleges and universities, as well as their political principals, often use classifications to form peer-groups and reference sets through which organizational performance is assessed. More broadly, classifications provide aspirational archetypes to an organizational field.

Using American higher education as the empirical context, this dissertation introduces Latent Profile Analysis (LPA) as a method to identify the structure of an organizational field and to classify organizations within this structure. Using measures of model fit and concerns for interpretability, this investigation determined that 13 distinctive organizational designs are present in the field of American higher education. Derived groupings are compared to the 2018 Basic Classification from the Carnegie Classification of Institutions of Higher Education. Opportunities and challenges for operationalizing this derived classification are discussed.

DEDICATION

I dedicate this dissertation to my family. I am greatly appreciative towards my mother and father, Barbara and Steven, and sister, Natalie, for all they have done to give me every opportunity to learn and grow.

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I would like thank Michael Crow, Derrick Anderson, and Spiro Maroulis for their support, feedback, and encouragement throughout my graduate school experience at Arizona State University.

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CHAPTER 1: INTRODUCTION

College and university classifications group organizations based on one or more organizational characteristics. Examples of classifications include sector (public, private not-for-profit, private for-profit), institution size, land grant status, historically black college or university status, and tribal college status. The 2018 version of the Basic Classification of the Carnegie Classification of Institutions of Higher Education uses several organizational characteristics to classify organizations and is the most used and influential classification in higher education (McCormick and Zhao 2005).

Higher education stakeholders use college and university classifications for a wide range of activities. Researchers investigating phenomena occurring in higher education settings often use classifications to create frames from which to draw samples of colleges and universities. Empirical studies that include colleges and universities from several classification categories often include classifications as control variables in models to hold constant unobserved organizational characteristics. Higher education stakeholders use classifications to form groups of colleges and universities for purposes of goal-setting and performance assessment. In these contexts, the analytic utility of a classification is directly related to its ability to create homogeneous groupings of colleges and universities from the heterogeneous field of higher education. The categories contained within a classification can also confer privileged status on members and cause the classification status of a college or university to become the object of strategic action.

College and university classifications have found little application in public policy. Despite these organizations being instruments through with policy makers realize public values, such as fostering intergenerational economic mobility or generating new knowledge that spurs economic advance and improvements in quality of life, many public policies pay little attention to the organizational designs of colleges and universities. When college and university classifications are used in public policies, they are often the broadest possible, such as sector. As such, the understanding that some college and university designs—as captured through a classification—might be better or worse than others at achieving important public values is not often incorporated in public policies.

The Carnegie Classification

History and Background

The Carnegie Foundation for the Advancement of Teaching established the Carnegie Commission on Higher Education in 1967 to advance recommendations to strengthen U.S. higher education. As part of the analytical work underpinning their policy recommendations, the Commission created a classification scheme of colleges and universities. Realizing the potential utility, the Commission published it in 1971 “to be helpful to many individuals and organizations that are engaged in research on higher education” (Carnegie Commission on Higher Education 1971). Carnegie has updated the “Basic Classification,” which is the most widely used classification among the various classifications they have created in 1987, 1995, 2000, 2005, 2010, 2015, and 2018. In addition to the Basic Classification, Carnegie produces specialized college and university classifications based on undergraduate instructional programs, graduate instructional programs, enrollment profiles, size and setting, and community engagement. The administration of the Classification is now housed at the Indiana University Center for Postsecondary Research (Indiana University Center for Postsecondary Research 2019).

Methodology of the 2018 Basic Classification

The 2018 Basic Classification uses an algorithmic approach with a series of yes/no questions to classify colleges and universities into discrete, pre-defined categories. There are currently seven categories and 27 sub-categories. The classification algorithm uses membership in the American Indian Higher Education Consortium, granting of degrees in only one academic field, and conferral of only associate's degrees to first classify institutions into Tribal Colleges, Special Focus Colleges, and Associate's Colleges categories. Institutions not classified into these categories are then classified into Doctoral Universities, Master's Colleges and Universities, Baccalaureate Colleges or Baccalaureate/Associate's Colleges categories based on the level of doctoral degree and master's degree production. Figure 1 provides the full classification algorithm of the 2018 Basic Classification as provided by the Indiana University Center for Postsecondary Research (Indiana University Center for Postsecondary Research 2019). Appendix A provides descriptive statistics for all subcategories in the 2018 Basic Classification.

The sub-categorization of the Doctoral Universities category, which is comprised of universities that confer more than 20 research doctorates or 30 professional doctorates per year, is noteworthy for its analytical complexity. Doctoral Universities that have less than $5 million per year in research expenditures are sub-categorized as Doctoral/Professional Universities. Doctoral universities with more than $5 million dollars in research expenditures are sub-categorized into High Research Activity Universities and Very High Research Activity Universities based on a “Research Activity Index.”

The Research Activity Index uses aggregate and per-capita full-time faculty data on 1.) science and engineering research expenditures; 2.) non-science and engineering research expenditures; 3.) science and engineering research staff (such as post-doctoral positions and non-faculty research staff); and 4.) research doctorate degree production. All data are converted to rank scores. Aggregate and per-capita data sets are separately analyzed with a principal components analysis. The first factors in each principal components analysis are used to create index scores for each university. These bivariate scores are plotted and universities are split into the High and Very High Research Activity subcategories based on their position relative to a line determined by the minima of each scale (Indiana University Center for Postsecondary Research 2019). Visual inspection of these bivariate score plots does not indicate obvious clusters of observations.

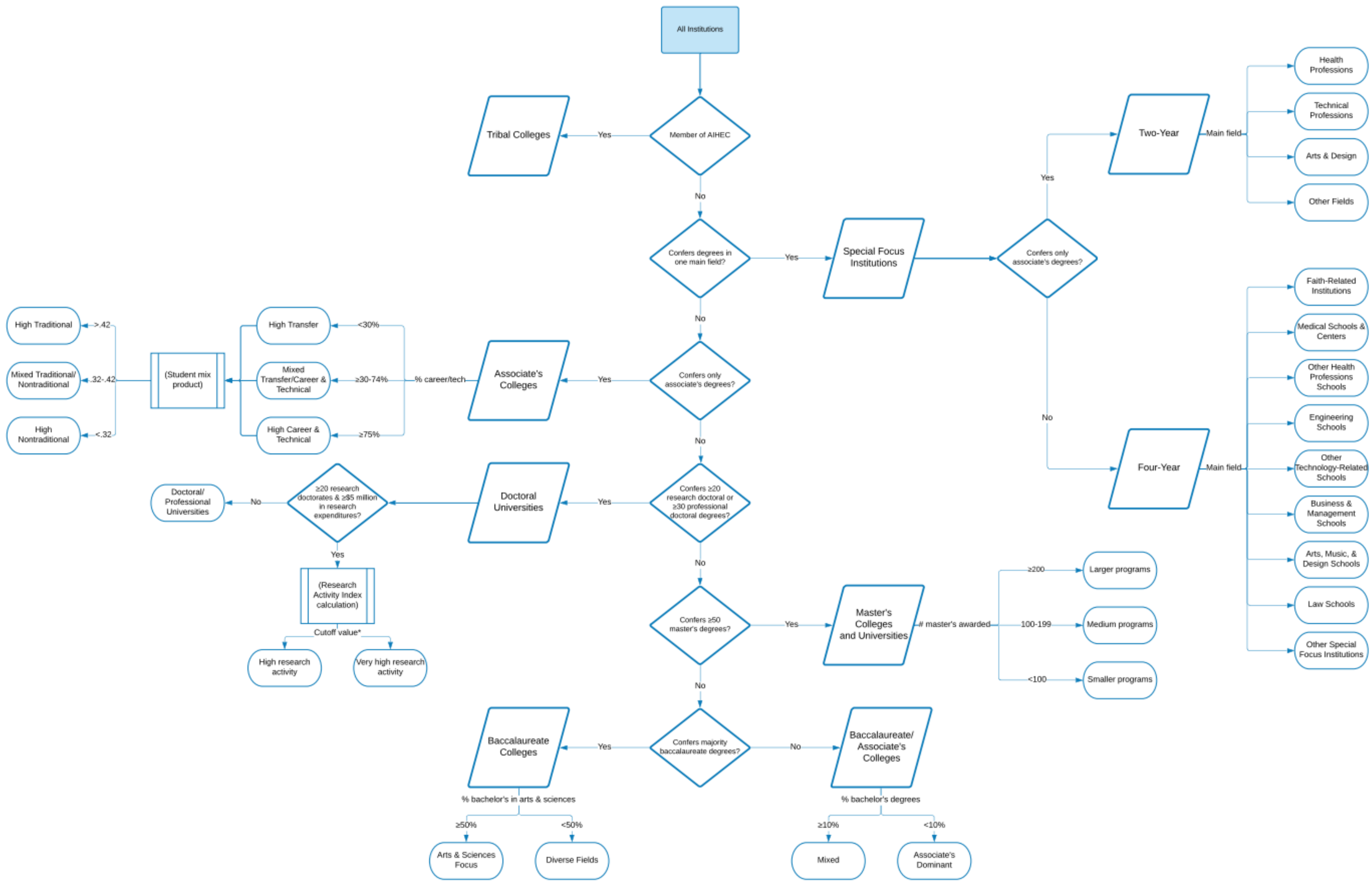
The methodology of the 2018 Carnegie Classification presents several concerns. First, the results are not fully reproducible by other researchers (Kosar and Scott 2018), despite the Indiana University Center for Postsecondary Research providing all underlying data on its website. This is largely due to the partitioning method used on Research Activity Index data. Harmon et al. (2019) report that Carnegie uses hand-drawn arcs to classify institutions “based on areas of ‘best separation’ in the groups.” Second, classification results are unstable from year-to-year. A change in an institution’s classification from one iteration of the classification to the next could occur for several reasons. Possibilities include changes in the variables used in the classification, changes in the variable thresholds in the classification algorithm, changes in the number of institutions meeting selection criteria for classification (which is particularly important in a relative-based classification procedure used on a small sample of institutions), changes in the physical shape of the particular hand-drawn arc used to partition doctoral institutions, and changes in university performance on the measured variables.

Impacts and Significance of the Basic Classification

Despite methodological concerns, the Basic Classification has had a significant impact on U.S. higher education. The effects largely stem from users of the classification interpreting the Carnegie Basic Classification subcategories as hierarchical and conflating classification with performance assessment. Educational administrators have characterized Carnegie R1 status as representing the “pinnacle of higher education—a shorthand for institutions to identify themselves” (Anderson 2016). Leaders in higher education often discuss achieving R1 status as a goal onto itself rather than a recognition that follows from pursuing other activities that support public value. Upon being classified as an R1 school in the 2018 update, a news release from Auburn University cited that achieving R1 status “has been a long-term goal for the university and one of the main priorities of President Steven Leath since he took office in March 2017" (Brownlee 2018). The University of Nevada-Las Vegas, which also achieved R1 status in the 2018 update, had long sought R1 status, and specifically created a plan to reach R1 status by 2025 (Solis 2018).

The instrumental value of the Basic Classification is often discussed in tandem with achieving a higher rank. In materials promoting consulting services to help universities "move up" and "climb" to a "higher" Carnegie Classification, one consulting firm implied a wide variety of benefits accrue from a higher Carnegie rank. These include an "enhanced institutional profile within their state and nationally, potentially greater state investment downstream, and the ability to attract and retain better faculty, students, donors, and partners" (Larme and Thayer 2017). Some rationalizations of reaching a higher Carnegie rank strain credulity. Villanova University claimed in a press release that the institution's "new Carnegie Classification…will increase the type of intellectual discussion that occurs among undergraduates, graduate students, and faculty on our campus" (Villanova University 2016).

Figure 1: 2018 Carnegie Classification: Basic Classification (reproduced from Indiana University Center for Postsecondary Research 2019)



Beyond the status and prestige accorded to highest-ranked colleges and universities, the classification status of an organization does have other material consequences. Grant-making foundations have linked grant eligibility to the Basic Classification status of an applicant's organization and state governments have used organizational classification status in various funding formulas (McCormick and Zhao 2005). Additionally, the ranking categories used by *U.S. News and World Report* directly map onto the categories of Carnegie's Basic Classification, which the publication refers to as the "accepted standard in U.S. higher education" (Morse, Brooks, and Mason 2019). Research has shown college rankings, such as those of *U.S. News and World Report*, to be predictive of a range of individual and organization-level outcomes (Rindova et al. 2018).

The identification of R1 as the pinnacle of higher education has focused the attention of university decision-makers on the specific metrics used in the Carnegie Classification. As universities have attempted to move up the hierarchy, they have spent real resources to affect these metrics. This has had a significant isomorphic effect on U.S. higher education, as universities direct resources to increase the scale and intensity of research expenditures and research doctorate degree production (McCormick and Zhao 2005). While few might argue that universities cultivating research expenditures or diverting resources to research activities and doctoral programs represents a critical failure of incentives, it does implicate the dual issues of opportunity cost of organizational design and the value of organizational diversity in a system of higher education. The Basic Classification, as consumed by external parties, provides one aspirational archetype for colleges and universities and does not capture the various ways in which colleges and universities build public value. For example, a college or university that broadens access and increases degree production for underrepresented minorities does not receive a “higher” ranking within the Carnegie Classification.

Purpose of the Present Study

The purpose of the current study is to explore organizational heterogeneity present in U.S. higher education. This study is focused on the following questions:

1. In what ways are four-year colleges and universities in the United States diverse in the ways they realize public value?
2. Can four-year colleges and universities in the United States be grouped to reflect their organizational designs?
3. What are the similarities and differences among and between these groups?
4. How do these groupings compare to existing classification schemes, such as the Carnegie Classification?

Significance of the Study

Generally stated, the purpose of taxonomy and classification is to evaluate observations within a heterogeneous population and assign them into homogeneous groupings based on their similarities and differences (Sneath and Sokal 1962). Within the context of higher education, the purpose of classification is to create groupings of colleges and universities that share similar organizational profiles across one or more attributes of interest. Clark Kerr described the original purpose of the Carnegie

Classification as the creation of groups that were "relatively homogeneous with respect to the functions of the institutions as well as with respect to characteristics of student and faculty members" (McCormick and Zhao 2005). The purpose of the present study is to advance an analytical method that creates groupings of colleges and universities with higher homogeneity and face validity than currently available classifications.

The accurate and meaningful classification of colleges and universities is critical to a variety of higher education stakeholders. Improved classifications can assist researchers examining higher education institutions as well as higher education administrators and political principals.

Academic Research on Higher Education

University classifications are widely used in academic research on higher education. They have been incorporated in several broad ways, including as a key explanatory variable, a control variable, and for sample selection. Examples of classifications being used as an explanatory variable include studies from the institutional characteristics literature, which often uses classification categories, such as those from the Carnegie Classification, in modeling outcomes, such as student graduation rates. This body of research has found weak evidence that institutional characteristics and institutional missions predict student outcomes when student characteristics are controlled (Pike, Kuh, and Gonyea 2003; McCormick et al. 2009). Examples of studies that use classifications to create sample frames include many studies from the extensive university technology transfer literature (Feldman et al. 2002; Friedman and Silberman

2003; Bozeman and Gaughan 2007). These studies have used classifications such as the Carnegie Classification, Land Grant status, and public status to select organizations for sampling.

When classifications are directly incorporated into empirical models of colleges and universities, their purpose is to capture unobserved organizational characteristics. In this way, classifications are critical: testing theories on well specified samples and with additional variables that meaningfully reflect institutional characteristics improves the ability of analytical methods to identify relationships between variables and improves the generalizability of the research.

University Strategy

Strategists and decision-makers act on taxonomic models of the competitive environment facing their organization. These can be mental models based on simple or sophisticated representations of environment (Porac and Thomas 1990) or predefined taxonomic models of industries or markets, such as the North American Industry Classification System (NAICS). Within the context of higher education, peer groups are often formed by geographic proximity, co-membership in athletic conferences, or Carnegie Classification (McKeown-Moak and Mullin 2014).

Taxonomic models and classifications directly connect to management strategy. They help organizational decision-makers define peer groups and develop mimetic or differentiating competitive strategies. They also can inform the creation of organizational goals, the assessment of organizational capabilities, and the identification of rivals.

Anachronistic classifications, on the other hand, can create competitive blind spots. Consider a contemporary automobile manufacturer that believes it has a strong position within the luxury automobile manufacturing market. The development of competing technologies, such as autonomous taxis, may change the competitive landscape such that the automobile manufacturer must compete not with the products of other luxury automobile manufacturers, but also entirely different forms of transportation.

Performance Assessment

University performance is a critical public policy issue. Each year, federal and state governments direct billions of dollars of public resources to public and private universities to provide access to higher education, to support critical research and development activities, and to perform a variety of other public service missions. Historically, state governments have supported public universities with block grants and/or enrollment funding instruments that determined appropriations based on student enrollment (Lumina Foundation n.d.). Recently, state governments have begun implementing performance-based funding policies that allocate some or all state funding to public universities based on university performance. Twenty-seven states have implemented these policies for four-year public colleges and universities (Dougherty et al. 2016). Although there is considerable diversity in the design and implementation of these policies, most of these policies seek to increase retention rates, graduation rates, and degree production (Harnisch 2011).

There is little evidence in the literature that these policies have been successful in achieving their aims. While some studies have found that the implementation of performance-based funding policies are associated with changes in resource allocations (Rabovsky 2012) and managerial decisions (Natow 2014), many studies have not been able to connect these policies to the achievement of university performance improvements such as graduation rates or degree production (Hillman, Tandberg, and Gross 2014; Rutherford and Rabovsky 2014).

Setting appropriate goals is a key to policy success. No known studies have examined the creation of specific goals in university performance-based funding policies. University performance—particularly within the domain of degree production and graduation rates—reflect the aggregate of individual student-level outcomes. Student-level outcomes, in turn, are a product of student characteristics interacting with the broader university environment (Tinto 2012). Within the language of a production process, this is to say that a university's output is a product of the university's inputs and its resource transformation process. Since the characteristics of students on "transformation processes" vary considerably across colleges and universities, it is difficult for oversight organizations to assess the performance of college or university: is a 60% four-year graduation rate for School X poor, adequate, or exceptional? Is School X's 60% graduation rate worse, similar, or better to School Y's 75% graduation rate? An improved classification of colleges and universities can help political principals assess and contextualize university performance by grouping similar schools together so that the performance of a college or university can be measured relative to the leaders, the laggards, and the average for other similar schools.

CHAPTER 2: LITERATURE REVIEW

Introduction

This chapter reviews the literature as it relates to the current study. The chapter begins by briefly defining and discussing the significance of taxonomy and classification within the enterprise of science. It then reviews taxonomy and classification within the organizational sciences before engaging and critiquing the modest academic literature that exists on the taxonomy and classification of colleges and universities. In search of new perspectives, this review then engages public administration's framework of realized publicness in order to inform a new approach to college and university taxonomy and classification.

Taxonomy, Classification, and Human Progress

Grouping entities—such as animals, plants, or sounds heard in the night—by their observed features is a fundamental cognitive behavior that helps humans quickly reduce the complexity of the natural world. This helps humans see patterns, hypothesize relationships, and build collective knowledge. Formalized versions of this activity include taxonomy, which is defined as the development of theories and methods for separating entities into groups, and classification, which is defined as the assignment of entities into formally designated groups (Sneath and Sokal 1962).

The history of taxonomy and classification is intertwined with the history of scientific and human progress. One of the first formalized classification structures of natural objects was Aristotle's *Scala Naturae*. This hierarchical classification ranked all living things known to Aristotle on a single continuum arranged by his assessment of their biological complexity and "potentiality" of reaching divine perfection (Granger 1985). Aristotle's classification reflected his view that living objects embodied essential, unchangeable characteristics that could be identified and compared. This fundamental assumption about the nature of living objects, which contemporary biologists have forcefully repudiated, had profound implications for those who used the *Scala Naturae* to guide research. Philosopher Karl Popper observed that any discipline that used Aristotle's method of classification "remained arrested in a state of empty verbiage and barren scholasticism, and that the degree to which the various sciences have been able to make any progress depended on the degree to which they have been able to get rid of this essentialist method (Popper 2012)."

Subsequent taxonomists have developed alternative theories of classification. These include nominalist approaches, which hold that groupings of entities do not naturally exist but rather are product of an individual's agency. Empirical approaches assume that natural groupings of entities exist and that analysis of observed data can reveal these natural groupings.

Empirical taxonomy and classification are critical in the use of the hypothetico-deductive method. Among other things, the scientific method requires the formulation of theories and falsifiable hypotheses, measurement of phenomena, and the public reporting of results for replication (Lawson 2015). Homogeneous groupings of observations assist in these activities, as they increase the ability of analytical methods to identify relationships within collected data and for other researchers to replicate results with other data. Without a robust and well-developed taxonomic and classification effort to proceed and ground empirical research, it is difficult for an investigator to know whether results are due to the idiosyncrasies of sample selection or the hypothesized theoretical relationships. In this way, taxonomy and classification are prerequisites of the scientific method rather than a product of it.

Organizational Taxonomy and Classification

Taxonomy and classification efforts in the organizational sciences are much more recent and less developed than in other fields. Bill McKelvey, writing in the early 1980s, described organization science as existing at that time in a pre-Linnean state: a "1750s body of knowledge cloaked in 1980s garb (McKelvey 1982)." A large part of this stems from a tradition of investigators using essentialist and special-purpose classifications that use a single organizational attribute to assign organizations to discrete categories. In the years after McKelvey published *Organizational Systematics* in 1982, there have been several notable large-scale classifications of organizations, such as research and development laboratories (Crow and Bozeman 1998), and several distinct lines of research have emerged.

One line of research engages organizational taxonomy and classification from a cognitive perspective. Largely using the language of "categorization" and rooted in psychology and sociology, this line of research views organizational categories as created by individuals for strategic purposes. Research in this line has focused on category emergence (Pontikes and Hannan 2014), category properties (Hsu and Hannan 2005; Hannan 2010), and the strategic use of categorization for competitive advantage within markets (Porac and Thomas 1990; Zuckerman 1999; Cattani, Porac, and Thomas 2017). This line of research emphasizes that categories are the artifact of individual agency.

A second line of work assumes organizational groupings exist beyond an individual's construction of them and views the purpose the taxonomic and classification research to identify these existing groupings. Drawing from phenetic classification in biology, this stream of research attempts to use the observed characteristics of organizations to derive groups of organizations that maximize organizational homogeneity within groupings and maximize heterogeneity across groupings. This research has largely focused on taxonomic methods and approaches. Research has addressed the interconnected issues feature selection, specification of sampling populations, and analytical methods. There has been disagreement in the role of theory in empirical classifications, which some authors arguing that empirical classifications should be unconstrained by prior theory (Rich 1992), while others argue that a purely inductive, theory-free approach to empirical classification is not possible (McKelvey 1982; Doty and Glick 1994). This line of research emphasizes the multidimensional nature of organizations: empirical taxonomic methods create polythetic groupings in which no single attribute is necessary or sufficient for an organization to be assigned to a group. Instead, a pattern of similarity across observed characteristics is needed.

Emerging Approaches to University Classification

A review of academic publishing databases finds a small and fragmented literature on college and university taxonomy and classification that is largely disconnected from theoretical work on organizational taxonomy and classification. One stream of this literature is focused on extending the logic of university classification to settings previously without traditions of university classification, such as South Korea (Shin 2009), Thailand (Phusavat et al. 2011), and India (Jalote, Jain, and Sopory 2020) or to explore the organizational diversity of small groups of colleges and universities serving specific purposes, such as Hispanic-serving institutions in the United States (Núñez, Crisp, and Elizondo 2016). Another stream of this literature, contributed to by scholars who administer the Carnegie Classification, attempts to reflect on the experience of creating the Carnegie Classification (McCormick and Zhao 2005; Indiana University Bloomington and McCormick 2013; Borden and McCormick 2019). A third stream of this literature directly engages, critiques, and attempts to improve upon the college and university classification efforts Carnegie started several decades ago. The present review will focus on this third stream within the literature.

This third steam of literature has focused more on broad taxonomic methods and approaches than the classification of specific colleges and universities into groups. As a result, a review of this literature must focus more on the limits and possibilities of the methods used rather than synthesizing the collectively derived knowledge of university forms. Among the studies reviewed, two studies focused on methodological improvements to the analytical procedure of the existing Carnegie classification system (Kosar and Scott 2018 and Harmon et al. 2019). Two other studies attempted new types of empirical classifications of research-intensive groups of colleges and universities. Brint and colleagues (2006) created aspirational reference sets for universities and colleges based on a survey of university presidents and compared these reference sets to an “objective” reference set derived from a cluster analysis of universities represented in their survey of university presidents. Crisp et al. (2019) used a k-means cluster analysis to find organizational groupings existing within the population of broad-access colleges and universities in the United States.

Theory

Organizational taxonomists have contested the role of theory in taxonomic work, with some authors arguing for a theory-free, inductive approach and others advocating for theory to provide the basis of feature selection and interpretation of results (McKelvey 1982). The studies reviewed here mirrored this debate and had significant differences in their engagement with theory. The two methodological papers ignored theory altogether, while the two classification papers had moderate grounding in theory.

Crisp and colleagues (2019) provided the strongest theoretical grounding. They used resource dependency theory to argue that differences in “systemic, constituential, programmatic, resource, and environmental” variables form the basis for understanding organizational diversity among broad-access institutions. Resource dependency theory, together with previous literature, led them to include 20 variables in their cluster analysis.

These ranged from performance outcomes, such as the retention and graduation rates, to environmental variables such as the unemployment rate and median housing prices in the surrounding county. They also included several existing classifications, such as institutional control and for-profit status, as measures.

Brint et al. (2006) provided less theoretical basis for their cluster analysis. They justified the inclusion of seven variables (Carnegie Classification, institutional control, total head count enrollment, average SAT/ACT test scores of admitted freshmen, undergraduate tuition, total organizational operating budget, and the percentage of degrees awarded in arts and sciences) as being "both central components of structural location and plausible bases for the formation of clusters…"

Samples and Data

All four studies engaged a limited sample of U.S. higher education. As methodologically oriented papers, Kosar and Scott (2018) examined doctoral institutions classified by Carnegie and Harmon et al. (2019) analyzed research-intensive universities classified by Carnegie. This limited their analyses to 276 and 334 universities, respectively, but allowed both groups to use the same dataset and measures used by Carnegie and to compare results to the Carnegie classification.

Brint et al. (2006) bounded their analysis to four-year and above public and non-profit private colleges and universities represented within the results of their presidential survey. Although their final sample included just 252 colleges and universities, their sample represented various types and kinds of colleges and universities present in

American higher education. Crisp et al. (2019) engaged the largest swath of U.S. higher education by sampling all public and private colleges and universities that had a freshman admissions rate of 80% or higher in 2014-15. This yielded a sample of 1,073 organizations, but excluded most of the largest and well-known universities in the country.

Methods and Results

Published papers on university classification have used a variety of analytical techniques to identify groupings of similar colleges and universities. Kosar and Scott (2018) and Harmon et al. (2019), which both focused on incremental improvements to the existing Carnegie methodology, employed a conceptually similar two-stage classification approach as Carnegie. They first applied a data reduction technique on aggregated and per-capita university data and then plotted resulting factors. Other authors have used data clustering methods such as k-means.

Kosar and Scott (2018) argued that Carnegie's approach of retaining the first component of two separate principal components analysis of aggregate and per-capita university measures does not optimally capture the variance occurring in the data. To explain more variance in the data, they applied a varimax rotation to the first two principal components of a combined aggregate and per-capita dataset. They then plotted these factors in X-Y space and used graphical boundaries to discretize the dataset into three groupings roughly corresponding to the doctoral, high-research activity, and very-high research activity categories in the Carnegie Classification. The resulting assignments of universities largely resembled the existing assignments from Carnegie. This approach suffers from several weaknesses. First, the there is no available measures of model fit beyond explained variation. Second, visual inspection of the plotted bivariate factors does not reveal any obvious clusters within the dataset. The assignment of universities into low, medium, and high groups is very sensitive to the graphical boundary lines, the placement of which are completely arbitrary.

Others have used methods, such as structural equation modeling, with additional diagnostic and model fit tools. Harmon et al. (2019) used the existing variables in the Carnegie dataset as items in a structural equation model that conceptualized STEM and non-STEM university productivity as two latent factors that, in turn, explained a shared latent factor of overall university productivity. This resulted in a single productivity factor score for each university, which the authors then ordered from lowest to highest. They used single-variable mixture modeling to derive three clusters present in the unidimensional dataset as well as to classify specific universities into these three clusters. This resulted in all 84 very high activity universities in 2015 Carnegie Classification clustering in their derived “SEM Large” category and approximately half of very high research activity universities and doctoral universities splitting between their “SEM medium” and “SEM small” categories.

Traditional clustering methods have also been used to classify universities. Brint, Riddle, and Hanneman (2006) used an agglomerative clustering method and the Akaike information criterion to derive seven clusters of colleges and universities present within their sample. Similarly, Crisp et al. (2019) used hierarchical agglomerative clustering on their sample of broad access universities. After using Box Cox transformations to normalize several variables, the authors analyzed public and private colleges and universities separately. AIC and BIC criteria indicated the presence of four clusters, which they identified as low-cost, open access public colleges; striving regional and state universities; private accessible liberal arts and religious colleges; and access-oriented minority-serving private colleges.

Conclusion

The papers analyzed here have several notable weaknesses. The two methodological papers conceptualize university differentiation based on a latent factor of university research productivity. Regardless of the particular data reduction and partitioning methods used, the conflation of university performance with organizational differentiation results in the studies creating a taxonomy of university performances rather than of organizational types that can inform the assessment of university performance. One of these studies (Harmon et al. 2019) explicitly created a hierarchical ranking of universities based on a latent factor of overall university productivity. The conceptual or practical utility of this ranking above a simple ranking of universities on any of the aggregate or per-capita variables is not clear.

Another critical issue with some of the reviewed studies is the inclusion of previous classifications, such as Carnegie classification and institutional control, as data on which universities groups are derived. With much of the observed variance across observations existing as prior university classifications, the inclusion of prior classification as data points increases the likelihood that the results of subsequent classification work simply recreate existing classifications.

Both of the issues above directly relate to the role of theory and the interpretation of results in these studies. Three of the papers reviewed had little to no grounding in theory and selected measures largely by convenience (such as selecting measures already gathered and publicly reported by Carnegie). This is an issue to the extent that the cluster analytical techniques used by these researchers will identify groupings of observations within multivariate databases, but will not ensure that resulting groupings are meaningful representations of organizational groupings as they exist and function in the organizational field. To ensure valid and meaningful results, investigators need to allow theory to guide the selection of measures and results need to be cross-verified with organizational field knowledge (McKelvey 1982).

Taken as a whole, these studies show a significant opportunity for additional research that is guided by theory, uses methods that provide diagnostics for model fit, and engages the totality of U.S. higher education rather than small, unrepresentative samples of colleges and universities.

Perspectives on Organizational Classification within the Field of Public Administration

This section engages and reviews the public administration literature, particularly the realized publicness literature, to provide a theoretical grounding for taxonomic and classification work of the present study. It begins with a discussion of various conceptualizations of organizational differentiation, including the generic approach and the core approach, before reviewing recent theoretical and empirical developments in the dimensional and realized publicness literature.

While the public administration literature does not often explicitly use the language of taxonomy and classification, these concepts have been central to the development of the field. The name itself—public administration—implies a type of classification of organizations based on some sort of attribute. Disagreements and debates as to these attributes constitute the basis of the publicness literature and the extent to which these attributes and resulting classifications cause differences in organizational outcomes is the foundation of the sector differences literature.

The Generic Approach

The generic approach negates substantive differences in public and private organizations. Rather than focusing on distinctive aspects of organizations, this perspective holds that organizational decisions are "subject to a cost-benefit calculus of one form or another and to a variety of competing inputs" (Scott and Falcone 1998) and that management practices can be developed or imported into organizations across sector without any significant revision or customization. Herbert Simon's theory of administrative behavior (1997), which places human cognition as the micro-foundation of organizational decision-making and ultimately organizational design, is an example of the generic approach. Key components of this theory, such as the worker program/script, are argued to exist in any type of organization. Despite being theoretically advanced by many early organizational scholars, there has been little embrace of this perspective by contemporary scholars who stress that public and private organizations are substantially different (Denhardt and Denhardt 2000).

The Core Approach

The core approach to understanding organizations, as characterized by (Bozeman 1987), stresses that differences between organizations arise from differences in organizational legal status. Scholars from a variety of fields, including economics, political science and public administration, have contributed to this approach but each differs in their theorizing as to how the legal status of an organization contributes to differences in manager and employee behavior as well as broader organizational outcomes. Despite their differences, these scholars often stress the categorization of organizations into discrete types. Scholars operating in this tradition have theoretically connected legal status to organizational behavior with property rights and political control arguments.

The property rights perspective of the core approach defines an organization's status as a function of ownership of the organization and sees differences in ownership as contributing to differences in employee and manager behavior. This perspective rests on the observation that individuals or other organizations can own private organizations directly. Ownership creates a very clear connection between management decisions and remuneration: it encourages owner/managers to focus on maximizing residual profits and increasing the long-term value of the organization by revenue generation, cost-cutting and productivity growth. Since ownership in public organizations cannot be transferred, managers lack incentives to provide “owner/entrepreneur oversight” (Bozeman 1987) of employees. These differences make private and public organizations substantively different.

Publicness: Dimensional and Realized

The dimensional approach departs from the core approach by stressing that differences between public and private organizations are only a matter of degree and that most organizations exist as hybrids on a public-private spectrum. This perspective, which was first advanced by Bozeman (1987) and later clarified by Bozeman and Bretschneider (1994), has spawned a diverse literature that is united in synthesizing both the economic and political control perspectives of the core approach and arguing that the concept can be applied to any organization in any sector. Bozeman (1987) summarizes the dimensional approach as classifying an organization as public “to the extent that it exercises or is constrained by political authority” and “private to the extent that it exercises or is constrained by economic authority.” In this way, the dimensional approach considers publicness as independent of the legal status of the organization.

While the dimensional approach to publicness combines both the economic and political approaches, it is more than a simple combination of them. Bozeman (1987) hypothesizes that several factors internal to the organization mediate the effects of external political authority. For example, existing endowments of political authority the organization holds can mediate impositions of new political authority on the organization. Levels of preexisting economic authority can mediate the impact of new impositions of external political authority. The level of "indigenous resources," such as "general competence and particular skills of management, level and flexibility of financial resources, composition of the labor force, reputation and general public perceptions, and supplies of natural resources and production inputs" (Bozeman 1987) can mediate external political authority. Boundary spanning by individuals within the organization can mediate the impact of external political authority on the organization by their ability to influence the broader operating environment or facilitate alternative resource acquisition strategies.

Moulton termed the stream of research flowing from Bozeman's (1987) dimensional approach as "descriptive publicness" since the traditional measures used in dimensional public research—funding, ownership, and control—are "intended to describe the characteristics that make organizations public" (Moulton 2009). Researchers, however, have used these operationalizations to predict certain organizational activities and outcomes. A review of the descriptive publicness research (Andrews, Boyne, and Walker 2011), found scattered evidence connecting the various dimensions of publicness to either organizational effectiveness or efficiency. A large issue is the operationalization of the dimensional publicness theory itself: many studies examined ownership, but not funding or control dimensions of publicness. The authors found that "public ownership leads to more equity and that public funding may be associated with higher efficiency," particularly in studies that were cross-sectional and that did not control for the internal or external context of the organization. The literature has not produced strong evidence that links dimensional publicness to organizational effectiveness.

It is against this backdrop that Bozeman (2007) and Moulton (2009) reframed dimensional publicness from descriptive publicness to "normative publicness" by using dimensional publicness to understand the extent to which organizations engage in behaviors that build public value. That is to say that the literature began to focus on public value achievement, termed "realized publicness" by Moulton (2009), as a dependent variable rather than dimensions of organizational publicness as independent variables to explain organizational effectiveness or efficiency.

Bozeman (2007) defined public values as those that provide "normative consensus about (a) the rights, benefits, and prerogatives to which citizens should (and should not) be entitled; (b) the obligations of citizens to society, the state, and one another; and (c) the principles on which governments and policies should be based." In this way, public values are not public goods in the conceptualization of neo-classical economic theory or simple public opinions. Public opinion shifts rapidly while public values evolve slowly. Public values can be found in a variety of sources, including founding documents of governments, laws, court decisions, national myths, and within public addresses by elected officials. Public values themselves cannot "fail," but a society can fail in the provision or realization of public values when "neither the market nor the public sector provides goods and services required to achieve public values" (Bozeman

2007). It is important to note that public values can be realized by actors in a variety of sectors and that their provision is not the sole responsibility of the state.

Moulton argued that realized publicness was a function of "public value institutions" that influence organizational behavior. These include regulative, associative and cultural/cognitive public value institutions. Although these concepts relate to the traditional measures of dimensional publicness, they are more encompassing. Regulative public value institutions include formal, legally sanctioned "rules, surveillance mechanisms, and sanctions that influence behavior." The theoretical link between regulative public value institutions and realized publicness can be made with institutional theory, principal-agent theory, or resource dependence theory. Associative public value institutions are not legally sanctioned. They include organizational membership in the "community, local networks, organizational affiliations, and certification agencies that may espouse public values and thus influence organizations toward realized publicness." Moulton points to institutionalism's isomorphic pressures on organizations to appear legitimate as linking the two concepts. The cultural cognitive dimension represents the perceptions and motivations of individuals operating within an organization towards supporting public value outcomes. In this way, Moulton explains realized publicness as a function of environmental, organizational, and individual-level variables.

Realized Publicness in Public Administration Research

This section engages and reviews the literature that has emerged in response to Moulton's (2009) framework of realized publicness as it relates to the present study. A search of Google Scholar for articles citing Moulton's framework reveals 192 articles, book chapters, and other published works. Of these, there were six articles written by a small and relatively integrated community of scholars that substantively engaged Moulton's framework with empirical investigations. The remainder of this section will review these articles with respect to their broad research questions, approaches to operationalizing concepts in the framework, and significant results. Their operationalization of realized publicness is of particular interest to the present study.

Most of the existing studies examine only certain aspects of the full framework of realized publicness in specific organizational settings. Moulton (2009) and Moulton and Bozeman (2011) investigated whether the environmental publicness of mortgage lenders influenced the provision of high-cost mortgages. Moulton and Bozeman (2011) conducted a multi-level analysis at the mortgage borrower-level and county-level using data collected from the 2004-06 HMDA Loan Application Register covering the states of Indiana, Ohio, and Florida. While Moulton (2009) did not conduct a quantitative study in her 2009 study, she did outline a possible study. Since her research proposal differs from the later operationalization, the paper remains instructive and is included here for that reason.

Several scholars have investigated realized publicness in the context of substance abuse centers. Miller and Moulton (2013) researched the connection between policy environments of substance abuse centers and organizational engagement in practices shown to improve client outcomes. While they did not explicitly use Moulton's (2009) framework of realized publicness, components of the framework are clearly present in the overall logic of the study and in the operationalization of the variables. Su (2016) also examined the impacts of political authority of "the provision of specialized programs for vulnerable groups" by substance abuse centers.

Feeney and Welch (2012) explored how dimensions of publicness observed at organizational and individual levels impact faculty behavior at research-extensive universities. Their study is the most complete investigation of the framework of realized publicness published to date.

Table 1 provides an overview of these studies.

Realized Publicness as Dependent Variable

Moulton (2009) identified the characterization of realized publicness—that is to say defining the public value of organizational outcomes—as the first step in applying the framework of realized publicness to an organization. The studies reviewed here vary with respect to how they did this: some focused on characterizing the behavior of an individual person, some focused on the presence of organizational engagement in an activity, and others focused on the degree of organizational engagement in an activity.

Feeney and Welch (2012) examined three dependent variables measured at the individual faculty level: the number of peer-reviewed journal articles published within the past two years, the number of courses taught within the past year and the number of committees served on within the past year. The authors justified the selection of these three variables based on faculty incentive structures at research universities being comprised of scholarship, education provision, and service dimensions. That is to say that these dependent variables are artifacts of the normative culture existing when these organizations first originated.

Several authors used dummy variables to capture whether an organization engaged in an activity deemed to realize public value. Miller and Moulton (2013) employed six dependent variables at the organizational level that included measures of both public service practices and positive client outcomes. All variables were dichotomous and included whether an organization served clients with (1) housing or with (2) employment; (3) utilized a case management system; (4) helped clients apply for other public social support services; (5) offered at some services free of charge; and (6) offered discounts to low-income clients. The authors motived the selection of these measures public values by citing previous research that has linked these organizational practices to long-term client outcomes. Su (2016), examining substance abuse centers, operationalized realized publicness with four dummy variables that captured whether a center offered specialized services for clients needing assistance for criminal justice; HIV/AIDS; pregnancy; or other co-occurring issues.

Other authors examined rates of engagement or levels of organizational outcomes. Within the context of mortgage lending, Moulton (2009) operationalized realized publicness as the percentage of a mortgage lender’s mortgages held by low-income borrowers as well as the payment delinquency and loan foreclosure rate of mortgages. She justified these particular outcomes based on decades of homeownership-related legislation, including the authorizing legislation of the Federal Housing Administration and other government-sponsored enterprises operating in the mortgage and housing industries, as suggesting that "increasing access to home ownership for 'underserved' populations" (Moulton 2009) is a key public value. Given the dual levels of analysis, Moulton and Bozeman (2011) constructed a multi-level analysis at the county and individual borrower-level that investigated whether an individual had a high-cost mortgage (defined as being more than "three percentage points above the comparable U.S. Treasury Rate"). This variable was operationalized as a binary variable and only represented the interest rate of the mortgage rather than other aspects of the loan, such as a points, fees, or presence of balloon payments. Although dichotomous, this variable within a geography represented the degree of organizations participating in an activity.

Continuous measures representing organizational degrees of engagement or activity are likely most consistent with the framework of realized publicness. After all, public value is not merely created by offering a service, but by ensuring that people can access or benefit from it. The two are not automatically linked. Individual-level measures, like those used by Feeney and Welch (2012), may be appropriate in organizational settings with high levels of front-line worker discretion or autonomy.

Significant Findings of the Realized Publicness Literature

The literature has used Moulton's (2009) framework in order to help understand how to manage for publicness. To this end, the authors have explained the realized publicness of organizations as a function of regulative, associative, and cultural/cognitive public value institutions. The theoretical links they argue, as well as the operationalizations of the three public value institutions, are beyond the scope of this literature review. Significant results will only be presented in summary. Overall, the studies found modest support for their hypotheses that the increased presence of regulative, associative, and cultural/cognitive public value institutions are linked to realized publicness.

Moulton and Bozeman (2011) found strong evidence that all three types of institutions influenced the realized public values of subprime mortgage lenders. Measures of associative publicness and two out of three dimensions of regulative publicness were statistically significant predictors of the probability of a mortgage holder having a high-cost mortgage. The only measure that was not significant was the presence of local nonprofit housing organizations.

Table 1: Realized Publicness Literature

	Research Questions	Analytical Method	Sector of Org	Level of Analysis	Dependent Variables	Regulative	Associative	Cultural/Cognitive
Moulton (2009)	"What influences make mortgage lenders more (or less) likely to provide for public outcomes?	Proposed statistical analysis (study not conducted)	Mortgage Lenders	Organization	Proportion of mortgages held by low-income borrowers and delinquency/foreclosure rates of mortgages	Lender contact with regulatory bodies	The degree of lender dependence community and extent of community organization	The "extent to which the lender shares public values of community "
Moulton and Bozeman (2010)	Does the "publicness of the lending environment at the county level" influence "the probability of a borrower receiving a high-cost loan…?"	Multilevel econometric regression	Subprime Mortgage Lending	County and individuals (mortgage holders)	Individual possessing a "high-cost" mortgage, binary	Extent of Mortgage Revenue Bonds in local mkt and "presence of nonprofit housing and community dev. orgs"	"Localness" of bank's lending activity	Not tested
Feeney and Welch (2012)	How do university "dimensions of publicness affect faculty behavior and outcomes?"	Hierarchical linear model regression	Research-Extensive Universities	Individuals (faculty members) and organization	Number of journal articles, courses taught within past year, and department/university committees served on in past year	Mixed	Mixed	Attitudes towards research and authority in department
Miller and Moulton (2013)	How does environmental and organizational publicness impact public service provision of substance abuse centers?	Hierarchical linear model regression	Substance Abuse Treatment Centers	States and organizations	Six variables of public service provision and positive client outcomes	Community publicness and public priority	Sector of organization	Not tested
Su (2016)	How do "different dimensions of political authorities facilitate the provision of specialized programs for vulnerable groups?"	Hierarchical linear model regression	Substance Abuse Treatment Programs	State and organization	Four dummy variables of facility offering specialized services	Collective publicness, revenue composition	Accreditation status	Not tested

Feeney and Welch (2012) found that regulatory publicness at the federal level was associated with increased knowledge and teaching outcomes while measures of state-based publicness only positively predicted service outcomes. Interestingly, state-based regulatory publicness was associated with lower levels of teaching publicness. Relative to normative and associative publicness, the authors found that the network size of faculty and affiliation with a federal laboratory positively related to knowledge outcomes. There was mixed evidence for the relationship between university association membership and knowledge outcomes and no support for their hypothesis that university commitments to diversity impacted faculty realization of education and service outcomes. There was mixed evidence of cultural and cognitive publicness impacting realized publicness. Faculty perception was not statistically significant in the prediction of number of faculty research articles published. An individual's perception of influence within a department, however, negatively predicted the number of courses taught and positively related to research output.

Miller and Moulton (2013) found largely supportive evidence. Associational publicness, as measured by organization sector, impacted the provision of all types of public service practices, with public organizations providing more than private organizations. Organizational receipt of public funding, regardless of sector, also increased the provision of public service practices. The two dimensions of regulatory publicness (collective publicness and public priority) were only statistically significantly connected to provision of certain types of public service practices.

Given the complexities and feedbacks of environments, organizations, and employees, moderation between public value institutions was a critical concern in several of the studies. Moulton (2009) started this community of scholars investigating these types of relationships by hypothesizing that associative variables might moderate regulative variables. In the case of mortgage lending, public disclosure laws force lenders to disclose public value realization (such as foreclosure rates) to the community in which they are embedded. The greater the extent lenders are embedded in a community that they must maintain good relations with, the higher the impact of regulation on the realization of public values. This thinking was confirmed in Miller and Moulton (2013), who found that regulative publicness moderated the relationship between associative (measured by sector) and public service provision. Private organizations in environments with high publicness behaved similarly to government and nonprofit organizations in the provision of public service practices.

Assessment of the Realized Publicness Literature

The realized publicness literature is largely characterized by consensus. A review of the literature reveals several important unifying trends around topical focus, methodology and theoretical perspectives. These trends represent strengths, weaknesses and opportunities for this literature.

All studies reviewed here examined organizations existing within a narrowly defined society-desired activity. Given that all studies operationalized the public value institutions differently and had at least one statistically insignificant outcome, it is not clear what results are idiosyncratic to particular organizational settings, such as substance abuse centers, and what results generalize to the large body of public organizations. Comparative research and multi-method research, such as case studies, could help provide clarity as to the critical bounds between the specific and the general.

Relatedly, these studies conceptualized the dimensions of realized publicness relevant to organizations as something to be separately and distinctly analyzed. This is related to these studies only engaging narrowly defined samples of organizations providing the same service, such as substance abuse counseling. It is not known whether realized publicness could be re-approached as a configural or combinatorial concept, in which organizations do not simply engage in more or fewer of activities that realize public value, but rather engage in different types of activities that realize different types of public value. This may be particularly useful in organizational fields that are broader and more complex or that allow organizations greater discretion in the types of activities they pursue.

The authors reviewed here also shared a common theoretical perspective: they connected public value institutions to realized publicness through institutional theory. This is to be expected, given the parallels of Moulton's public value institutions to DiMaggio and Powell's (1983) three forces of isomorphism: regulative, associative, and cultural public value institutions cleanly map onto coercive, mimetic, and normative isomorphic pressures. While accessing DiMaggio and Powell's logic has allowed this community of scholars to justify the relationships of these public value institutions to realized publicness, it has also locked them into an exploration of homogenization. Reframing the focus toward issues of divergence and heterogeneity might prove fruitful in that this focus could help identify conditions in which organizations evolve, change, innovate, or otherwise differentiate themselves in the face of pressure to converge.

Realized Publicness of Higher Education Organizations

This section of the literature review will address the ways in which colleges and universities realize public outcomes. This is not an insignificant task, as organizational diversity and complexity characterize the higher education system in the United States. It has evolved over three centuries from a small collection of church-affiliated colonial colleges to an array of over 4,360 organizations. These include organizations popularly classified as public, private, and for-profit schools; two-year, four-year, and graduate-only schools; teaching-focused and research-focused schools; regional, access-oriented public schools and nationally-oriented flagship public schools; theological seminaries; public and private trade schools; and large elite private colleges. This collection of organizations is economically and socially important: as a whole, colleges and universities expend more than $596 billion on operations, enroll over 19 million students, employ 1.5 million faculty and staff, and grant 1.96 million bachelor’s degrees and 2 million other academic degrees and credentials per year (NCES National Center for Education Statistics 2018).

The first step in determining realized publicness in the framework that Moulton (2009) advances is to identify the public values that organizations in a particular setting are able to achieve. Public values, as defined by Bozeman (2007), provide “normative consensus about (a) the rights, benefits, and prerogatives to which citizens should (and should not) be entitled; (b) the obligations of citizens to society, the state, and one another; and (c) the principles on which governments and policies should be based.” They are found in a variety of sources, such as authorizing legislation, laws, court decisions, national myths, and public addresses by elected officials.

Access to Learning Environments

Colleges and universities have been definitionally associated with the provision of access to learning opportunities, although broad attitudes as to the groups of students to which this access is provided has evolved over the centuries. Harvard Corporation, which was the first organization of higher education created in the American colonies, was founded by vote of the Great and General Court of the Massachusetts Bay Colony in 1636 out of a collective impulse to not only replicate storied English institutions in a new, unsettled environment but also to support an aristocratic class that would spur broad social development (Harvard University n.d.). The 1780 constitution of the Commonwealth of Massachusetts contained an entire chapter concerning “the university at Cambridge” and specified that “…it shall be the duty of legislatures and magistrates, in all future periods of this commonwealth, to cherish the interests of literature and the sciences, and all seminaries of them; especially the university at Cambridge (M.A. Const. Ch. 5, §1, art. I, 1780).” In the following decades, many states chartered and funded universities through their constitutions to support expanded access to higher education (Rudolph 1962).

Several pieces of legislation passed in the middle and second half of the twentieth century clarify modern public values in higher education, particularly as it relates to the provision of educational access to low-income and other historically under-represented groups of learners. The various “G.I. Bills” passed since 1944 have provided financial assistance to veterans and servicemembers to attend college (*Servicemen’s Readjustment Act of 1944* 1944) and the Higher Education Act of 1965 established grants and loans to assist low-income students in attending colleges and universities (*Higher Education Act* 1965).

Policy debates at the state level are also insightful. In 2016, the California State Auditor determined that the University of California system had done “significant harm to residents and their families” by decreasing resident enrollment by 2,200 while growing nonresident and international student enrollment by 18,000 from academic year 2010-11 to 2014-15; reducing admissions requirements for nonresidents; not adequately containing costs; and not fully investigating cost-cutting measures before raising tuition on resident students (California State Auditor 2016). Criticism from policy elites has defused out to the broader public and provides evidence as to public values: a Pew Research Center study found that 57% of Americans thought “the higher education system in the United States fails to provide students with good value for the money” (Pew Research Center 2011).

Creating an academic environment conducive to student success is another way colleges and universities realize public value. The Higher Education Act of 1965 established federal grants to small and less-developed colleges and universities to "assist in raising the academic quality of colleges which have the desire and potential to make a substantial contribution to the higher education resources of our nation…" It also established a $50 million fund to assist college and university libraries in acquiring "books, periodicals, documents, magnetic tapes, phonograph records, audiovisual materials, and other related library materials" to enrich the environment in which students learn (*Higher Education Act of 1965* 1965). These provisions suggest that colleges and universities realize public value by not only admitting students but also designing an instructional and broader academic environment in which students can succeed.

Production of New Knowledge

Debates over the role of knowledge production in U.S. colleges and universities date back to the middle of the 19th Century and the establishment of German-influenced universities such as Johns Hopkins in 1876 (Cole 2010). Combining the functions of knowledge transmission and stewardship with knowledge generation required significantly different organizational designs. That these new organizational designs realized new types of public outcomes has been recognized in a range of federal legislation. This legislation has resulted in the federal government spending $40.94 billion on university-based research and development in FY2017 (AAAS 2020).

These ongoing public investments in university-based research and development date back to *Science, the Endless Frontier,* a document written by Vannevar Bush that has served as the blueprint for the modern relationship between the federal government and the enterprise of scientific and technological research (Cole 2010; M. M. Crow and Dabars 2020). Writing at the end of the Second World War and buoyed with the public successes of the Manhattan Project and the mass production of Penicillin, Bush argued that the continued federal funding in times of peace would help in the war against disease, would improve national security and would improve public welfare through the creation of new industries and jobs (Bush 1945). Given that addressing grand challenges requires society-wide efforts, this study will consider the organization-level generation of new knowledge to be a realized public outcome.

This review suggests that colleges and universities realize public outcomes in three broad ways: the provision of student access to undergraduate and graduate learning environments, the provision of an academic environment conducive to student success, and the generation of new knowledge.

CHAPTER 3: METHODOLOGY

This research seeks to address and explore several related research questions:

1. In what ways are four-year colleges and universities in the United States diverse in the ways they realize public value?
2. Can four-year colleges and universities in the United States be grouped to reflect their organizational designs?
3. What are the similarities and differences among and between these groups?
4. How do these groupings compare to existing classification schemes, such as the Carnegie Classification?

This chapter will discuss the empirical strategy employed to answer these questions. It will first address the complexities of the sample specification before describing the manifest variables and statistical method used in the present study.

Population, Data Source, and Sample

The population for the present study is comprised of all four-year colleges and universities in the United States. Both data limitations and availability dictate the specification of the final sample. The data for this study come from two sources. First, I use data from the Integrated Postsecondary Education Data System (IPEDS) of the U.S. Department of Education (National Center for Education Statistics 2020b). This survey-based administrative dataset contains annual data on student enrollment, student outcomes, faculty and staffing, price, cost, and other institutional characteristics for all institutions in the United States and abroad that participate in Title IV federal financial aid programs. Institutions calculate and report these data and the U.S. Department of Education audits and verifies reported data. Second, I use data from the Indiana University Center for Postsecondary Research, which currently administers the Carnegie Classification (Indiana University Center for Postsecondary Research 2019). This includes university research expenditure data from the National Science Foundation's Higher Education Research and Development (HERD) survey that the Indiana University Center for Postsecondary Research has mapped onto the smaller units of analysis present in the IPEDS database.

The sample for the present study attempts to balance comprehensiveness with comparability, as determined by data limitations inherent in the study of organizational diversity. Institutions populating the landscape of higher education in the United States have large differences in organizational inputs, educational processes, financial models, oversight mechanisms, organizational lifespans, and outputs. While these differences can be important and useful in categorizing these organizations, they can also impose significant limitations on the data available to study them.

A critical issue that data limitations may create is false equivalences. For example, a researcher may be interested in understanding the degree of access that institutions provide to lower-income students. There are very few measures of this critical concept available, with Pell student enrollment being one of the most commonly used. An institution that only operates a graduate medical program would appear as having no Pell student enrollment and could appear analytically similar to a small, highly exclusive college that enrolls few lower-income students. Yet, this is not necessarily because the medical school is not providing access to lower-income students like the exclusive college, but rather because the medical college does not enroll undergraduate students and only undergraduates are able to qualify for Pell grants.

The issues data availability create require careful and attentive consideration and inform the sample selection of the present study. In cases where data availability issues would likely misrepresent the nature of organizational diversity, organizations with certain identified characteristics were excluded to minimize that misrepresentation. These exclusions were relatively rare and limited in nature, and resulted in a large overall sample for analysis.

The final sample was limited to all colleges and universities present in the IPEDS database that are eligible to receive Title IV federal financial aid, are under public or private not-for-profit control, located in a U.S. state, enroll first-time full-time (FTFT) freshman undergraduates, charged an annual tuition of a least $1 in 2017-18, granted more than ten bachelor's degrees in 2017-18, and offered at least some educational programs on a face-to-face basis. These restrictions ensure sufficient data availability for organizational comparison. The final sample consisted of 1,620 colleges and universities that enrolled 8,736,103 undergraduates and 2,499,146 graduate students in 2018-19.

Unit of Analysis

Specifying an appropriate unit of analysis, often referred to as an Operational Taxonomic Unit (OTU), is critical in taxonomic and classification work (Sneath and

Sokal 1962). Within an organization research context, an OTU could be a group of employees, a department, a legally recognized corporate entity, or an entire industry. A key consideration in selecting organizational OTUs is that they are measured consistently across the sample and are directly connected to the research question (McKelvey 1982; Rich 1992).

American institutions of higher education are designed, managed, and assessed at various levels of aggregation and scale. Depending on the organization, these concentrically nested scales can include the student-instructor dyad, class, individual academic program, department or academic unit, child campus/UnitID campus, parent campus, OPEID, and university system. Decisions occur and data are collected at various levels of this hierarchy.

The IPEDS dataset observes at the "UnitID" level. Although it does not provide a definition for UnitID (National Center for Education Statistics 2020b), UnitID often corresponds to geographically discrete campuses that are separately accredited by an accrediting agency. California State University-Dominguez Hills and Yale University are examples of entities that have a unique UnitID within IPEDS. IPEDS provides variables that researchers can use to aggregate UnitID-level data into alternative levels of analysis.

The first alternative is aggregate UnitID-level data up to the OPEID level. Organizations that are eligible to receive Title IV federal student financial aid have program participation agreements with the U.S. Department of Postsecondary Education. Each campus that has a participation agreement with the Department of Education has a unique OPEID (Kelchen 2017). Universities with multiple campuses can have a single program participation agreement and a single OPEID despite having multiple accredited campuses within the organization. Arizona State University is an example of an organization with a single OPEID and multiple campuses with distinct UnitIDs. Since no data is reported at the OPEID level, users wishing to use OPEID-level data must collect count data at the UnitID level and aggregate them into a new unified OPEDID-level organization.

A second alternative is to use “parent” campus level data. The Department of Education allows colleges and universities to report data to IPEDS on a parent/child campus basis (National Center for Education Statistics 2020b). The decision to use this type of data reporting is at the discretion of the college/university and is often used for reporting certain financial data such as state appropriations (Kelchen 2017; Jaquette and Parra 2014). When this reporting method is used, data for smaller campuses/branch campuses are aggregated up and reported by a single campus in the university system, most often the largest campus within the system, and smaller campuses report no data for that variable. IPEDS provides a parent-child factor for campuses subject to this reporting so that analysts can reallocate data from the aggregated “parent” campus to the smaller “children” campuses.

A third alternative is to use the multi-campus identifier within IPEDS. This variable, which is not explicitly defined in the IPEDS glossary, provides detail on whether a college or university campus is organized within a larger organizational unit.

Inspection of the dataset shows that this variable is irregularly coded within IPEDS and of questionable utility. For example, IPEDS classifies the ten campuses of the University of California as belonging to the “University of California” system, but the campuses of Arizona State University, Northern Arizona University, and the University of Arizona as belonging to the “Arizona Board of Regents” system. While the campuses of the University of California share a single Board of Regents and university president and have centralized student admissions, human resources, and other university administrative activities (University of California 2020), the three public universities in Arizona only share a common oversight board. All other university activities occur separately within the universities. Thus, the multi-campus variable in IPEDS may inadvertently commensurate very different organizational hierarchies.

There are benefits and drawbacks with using each of these units of analysis. Using either the OPEID or multi-campus approach eliminates the use of variables in the IPEDS universe reported only as rates, such as many distance education enrollment and graduation rate measures, since these measures cannot be reconstructed at a higher level of analysis without count data. More importantly, the creation and use of these levels of analysis may also create units of analysis that are not functionally relevant to a taxonomic study: they may create “synthetic” organizations that do not correspond to how these organizations function and create value for students and the broader public. For example, with respect to the student experience, aggregating a small, rural branch campus of a major research university with the much larger research-intensive campus of that university analytically treats the branch campus students as learning within the environment of the larger campus. The campus environments of the two campuses are unlikely to match, so aggregation is likely to create misrepresentations of reality.

This study attempts to balance the preservation of the smallest possible unit of analysis while ensuring data availability and accuracy. As such, this study observes at the UnitID level and uses IPEDS-created parent/child reporting factors to portion financial data calculated at the parent-campus level down to the child-campus level.

Variables Used in Study

This section details the variables used in the present study. The combined IPEDS/IUCPR/NSF dataset contained hundreds of plausible measures of organizational engagement in activities that could realize public values. It would be undesirable to include all possible measures, as many of these are highly correlated and LPA models can be become difficult to estimate with high numbers of manifest variables. As such, a subset of measures was selected from the dataset based on several criteria. These criteria included data availability across the sample, use in previous studies, and uniqueness. Underlying the selection of these measures is also the fundamental assumption that they reflect conscious or unconscious decisions of these organizations (or their principals) in reference to organizational goals and objectives and are, as such, indicators of organizational designs.

Many of these variables have been created or normalized with additional variables to improve their analytical utility. For example, the under-represented minority student calculation contains six variables from IPEDS. As such, many of the measures used in this study do not appear as single variables in the cited data sources. Their description below is intended to both explain the utility of these variables in representing activities that could build public value as well as to provide sufficient detail for subsequent researchers to recreate them. The Stata code for this study, including the code that creates and transforms variables collected from the data sources, is available upon request from the author. Table 2 below provides descriptive statistics as well as the underlying source for each variable used in this study.

Admissions Rate, Percent

The admissions rate is calculated by dividing the number of freshman students admitted for Fall 2017 by the total number of number of students who applied for freshman admission for Fall 2017. The variable reflects the capacity of an institution to accommodate learners who are interested in attending that institution.

Undergraduate Enrollment, Count

This variable captures the total headcount enrollment of undergraduate students in Fall 2017. It represents the general scale of access that a college or university provides society to an undergraduate education.

Graduate Enrollment, Count

This variable reflects the total headcount enrollment of graduate students in Fall 2017 and captures the scale of access that a college or university provides society to graduate education.

FTFT Enrollment, Percent

A first-time, full-time student is an undergraduate student who has not previously attended an academic or occupational program at any postsecondary institution and enrolls in a degree-seeking program as a full-time student (National Center for Education Statistics 2020b). Most outcome measures, such as the retention rate and graduation rates, are calculated based on the outcomes of this group of students. These students represent the "traditionality" of the student body. College and universities that serve distance education, adult/returning, and other types of non-traditional learners often have low rates of FTFT enrollment.

Under-represented Minority Student Enrollment, Percent

This variable represents the percentage of the undergraduate enrollment of a college or university that this comprised of learners from the following racial/ethnic backgrounds: American Indian or Alaska Natives; Black; Hispanic of any race; Native Hawaiian or other Pacific Islander; and students of two or more races.

Enrollment of Pell Grant Enrollment, Percent

Pell student enrollment captures the percentage of undergraduate students who received a Pell grant in the 2017-18 award year. It is calculated by dividing the number of undergraduate students who received Pell grants in the 2017-18 by the revised undergraduate financial aid cohort of 2017-18. The Pell program is a Title IV Federal Financial Aid program designed to provide students from lower-income families with grants to attend an undergraduate institution. This variable captures the intensity or rate of access that a college or university provides to learners from lower-income families.

FTFT Student Geographic Concentration, HH Index

This variable captures the geographic concentration of FTFT students. It is calculated as a Herfindahl-Hirschman (HH) Index. The number of FTFT students from each U.S. state and the District of Columbia are converted into shares relative to the total enrollment of FTFT students from each U.S. state and the District of Columbia. The shares for each geographic unit are then squared and summed for each institution. As such, this measure hypothetically ranges from 196.07 to 10,000: an institution that enrolls one student from each U.S. state and the District of Columbia would have an HH Index value of 196.07 (complete dispersion) while an institution that enrolls one student from one state would have an HH Index of 10,000 (complete concentration).

Tuition and Fees, Dollars

This variable is the published tuition and fees for in-state (if applicable) undergraduate students in the 2017-18 academic year.

Net Price, Dollars

This variable is the average net price of attendance in 2017-18 for in-state (if applicable) undergraduate students coming from families making less than $30,000 per year.

Instructional Expenditures, Dollars

This variable is a measure of the total instructional expenditures in FY2018 divided by the total undergraduate and graduate student headcount in 2017-18. Instructional expenditures include all resources that a college or university expends on credit and non-credit instruction for general academic, occupational, and vocational instructional activities.

Number of Undergraduate Degrees Offered, Count

This variable measures the number of bachelor's degrees offered by a college or university at the four-digit (Classification of Instructional Program) code level. The CIP is a taxonomy of academic fields of study created by the National Center for Education Statistics of the U.S. Department of Education (NCES 2020). Examples of four-digit level fields of study within this taxonomy include Public Policy Analysis; Mechanical Engineering; Social Psychology; and Finance.

Bachelor's Degree Production, HH Index

This measure reflects the concentration of bachelor's degree production by two-digit CIP field of study expressed in terms of a Herfindahl-Hirschman Index. Examples of two-digit CIP codes include Public Policy, Engineering, Psychology, and Business (NCES 2020). To calculate this index, the number of degrees produced in each two-digit CIP code are converted into shares relative to the total bachelor's degree production of the college or university. The shares for each two-digit CIP code are then squared and summed for each institution. Given that there are 37 two-digit CIP codes, this measure ranges from 270.27 (complete dispersion across two-digit CIP codes) and 10,000 (complete concentration in a single two-digit CIP code). This is a measure of the comprehensiveness of a college or university's academic enterprise.

Tenure and Tenure-track Faculty, Percent

This variable measures the percentage of tenure and tenure-track faculty as a percentage of total instructional faculty at a college or university in 2017-18. Tenure and tenure-track faculty positions are characterized by their permanence (National Center for Education Statistics 2020b). Directly related to notions of academic freedom, the presence of tenure and tenure-track faculty captures the extent to which a college or university provides "conditions conductive to scholarly work" and is committed to the community of scholars (Metzger 1961; Rudolph 2011).

Science and Engineering Research Expenditures, Thousands of Dollars

This variable reflects the sum of FY17 research expenditures at a college or university in the fields of computer and information sciences, geosciences, life sciences, agricultural sciences, biological and biomedical sciences, health sciences, mathematics and statistics, physical sciences, chemistry, physics, psychology, and social sciences. The data source is the National Science Foundation's Higher Education Research and Development Survey. Campus-level figures are estimated from the system-level NSF data by multiplying system-level figures by the percentage of faculty at a campus relative to the total number of faculty within the university system. Campus-level figures are provided by the Indiana University Center for Postsecondary Research (Indiana University Center for

Postsecondary Research 2020). This measure is reported as an aggregate dollar figure and captures the scale of knowledge production in the sciences.

Non-Science and Engineering Research Expenditures, Thousands of Dollars

This variable is the sum of FY17 research expenditures at a college or university in the fields of business management in business administration, communication, education, humanities, law, social work, and visual and performing arts. The data source is the National Science Foundation's Higher Education Research and Development Survey and campus-level data are provided by the Indiana University Center for Postsecondary Research (Indiana University Center for Postsecondary Research 2020). This measure is reported as an aggregate dollar figure and captures the scale of knowledge production in non-science academic fields.

PhD Offerings, Count

This measure is the number of disciplines in which a college or university granted a research/scholarship doctoral degree in 2017-18. A research/scholarship doctoral degree program requires "advanced work beyond the master's level, including the preparation and defense of a dissertation based on original research" (National Center for Education Statistics 2020b). This contrasts with professional practice doctoral degrees, such as a Doctor of Medicine or Juris Doctor, which provide knowledge and skills directly connected to the practice of a licensed or credentialed profession. Since Yale awarded the first Ph.D. degree in 1861, the presence and scale of research/scholarship doctoral degree programs at a college or university has been seen as a key organizational differentiator and driver of value to academia and broader society (Rudolph 2011).

Table 2: Descriptive Statistics

Variable	n	Mean	Std. Dev.	Min	Max	Source
Student Access						
Admissions Rate, Percentage	1,620	0.69	0.21	0.03	1.00	IPEDS
Students Enrolled in Distance Education, Percent	1,620	0.23	0.24	0.00	1.00	IPEDS
Undergraduate Enrollment, Count	1,620	5392.66	8141.65	39.00	83544.00	IPEDS
Graduate Enrollment, Count	1,620	1542.68	2957.31	0.00	29290.00	IPEDS
FTFT Enrollment, Percent	1,620	0.20	0.07	0.00	0.41	IPEDS
Under-represented Minority Student Enrollment, Percent	1,620	0.29	0.21	0.00	1.00	IPEDS
Pell Grant Enrollment, Percent	1,620	36.84	15.78	0.00	100.00	IPEDS
FTFT Geographic Concentration, HH Index	1,620	5477.73	2810.43	422.46	10000.00	IPEDS
Learning Environment						
Net Price (Family Income>$30k), Dollars	1,620	15634.10	7249.89	-3260.00	54584.00	IPEDS
Tuition and Fees, Dollars	1,620	23549.24	14319.26	1020.00	57208.00	IPEDS
Instructional Expenditures per Student, Dollars	1,620	10421.72	9234.42	0.00	129954.50	IPEDS
Number of Bachelor’s Degree Offerings, Count	1,620	31.39	19.00	1.00	111.00	IUCPR
Bachelor's Degree Production, HH Index	1,620	2301.99	2353.83	578.71	10000.00	IPEDS
Knowledge Enterprise						
Tenure and Tenure-track Faculty, Percent	1,620	0.57	0.34	0.00	1.00	IPEDS
Science and Engineering Research Expenditures, Dollars	1,620	37091.55	156643.80	0.00	2556641.00	NSF/IUCPR
Non-Science and Engineering Research Expenditures, Dollars	1,620	2416.34	9841.52	0.00	126607.00	NSF/IUCPR
PhD Degree Offerings, Count	1,620	2.26	5.07	0.00	25.00	IPEDS

Statistical Method

There are a variety of methods to identify groups of similar entities within multivariate datasets and assign members to these groups. These approaches can be understood as existing on a spectrum ranging from inductive-oriented methods to deductive-oriented methods (Schmiege, Masyn, and Bryan 2017). Deductive-oriented methods are ideal for confirmatory research that seeks to test hypotheses in the context of a theoretical model. Methods that specify the number of groups present within a population, such as confirmatory latent class analysis, are examples of deductive-oriented clustering methods. Inductive-oriented methods, often characterized as data-driven or bottom-up methods, are largely applied in exploratory settings. Inductive methods allow researchers to analyze datasets without prior theoretical expectations on phenomena, such as the number of groups present. K-means clustering and latent class analysis are examples of inductive methods.

Latent Class and Latent Profile Analysis

Latent class analysis (LCA) is a statistical method to determine groups of unobserved heterogeneity within populations (Lazarsfeld 1968; Nylund-Gibson and Choi 2018). Although the term "latent class analysis" has been generically applied to models using either continuous or categorical observed variables, latent class analysis applies only to models that use categorical observed variables to classify observations into classes. The classic two-by-two matrix popularized by management consultants is a simple example of latent class analysis (Goodman 2002). Latent models that use continuous observed variables are called latent profile models (LPAs). Figure 2 shows the relationship of these models to other common mixture models.

Figure 2: Mixture Models

		Latent Models for Means	
		Continuous	**Discrete**
Observed Variables	**Continuous**	Factor Analysis	Latent Profile Analysis
	Discrete	Item Response Theory	Latent Class Analysis

Both LCA and LPA have been widely used in the social sciences and medicine. For example, researchers have used LCA and LPA to classify types of children who present for mental healthcare (Petersen, Qualter, and Humphrey 2019), types of family-owned firms (Stanley, Kellermanns, and Zellweger 2016), and types of customers in a market (Oberski 2016). Within the domain of education, researchers have used these methods to create typologies of students at four-year institutions (Dugan 2011), two-year institutions (Hum 2016), as well as leadership types of principals of primary and secondary schools in the U.S. (Urick and Bowers 2014).

LCA and LPA models conceptualize class membership as a latent, or unobserved, categorical variable present within a population (Goodman 2002; Nylund-Gibson and Choi 2018). The fundamental premise of these models is that covariation between observed measures is explained by the latent group membership. These methods use multivariate datasets to estimate the number of classes present in the sample, the probability of each observation belonging to each class, and the relative size of each class. They can be used in both confirmatory and exploratory research.

There are a number of advantages of LCA and LPA relative to other cluster analysis methods, such as k-means. LCA and LPA do not necessarily require variable standardization, are less affected by variable multicollinearity than other cluster analysis methods (Stanley, Kellermanns, and Zellweger 2016), and are able to accommodate different distributional assumptions of manifest variables within the structural model (Bauer and Curran 2004; Masyn 2013; Nylund-Gibson and Choi 2018). LCA and LPA use a maximum likelihood estimation with an expectation-maximization procedure, which allows for observations with missing data to be analyzed. Further, LCA and LPA estimations result in group membership probabilities. These probabilities, unlike discrete group assignments, can help illuminate the relationships between groups and identify observations that are marginally attached to a group.

The equations estimated in latent profile analysis were developed by Lazarsfeld (1968). The general form of these equations, given in Vermunt (2004), explains the joint distribution of manifest variables as a mixture of class-specific manifest variable distributions:

$$f(\mathbf{y}) = \sum_{x=1}^{C} P(x)\, f(\mathbf{y}|\mu_x, \mathbf{\Sigma}_x).$$

In the equation above C represents the number of classes, μ_x is the mean vector of latent class x, and Σ_x is the covariance matrix. The assumption of local independence, and thus, equal error variances across classes, yields:

$$f(\mathbf{y}) = \sum_{x=1}^{C} P(x) \prod_{\ell=1}^{L} f(y_\ell | \mu_{\ell x}, \sigma_{\ell x}^2).$$

Principled Model Building

In exploratory research with latent profile models, the number of classes present within a population is not known *a priori*. The LPA literature recommends iterating through the steps of principled model building to increase the reliability and validity of the analytical results. This entails completing the steps of model specification, model identification, and class enumeration before proceeding to classification.

Model specification involves specifying the measurement model in the structural model, including the family and linking functions appropriate for the manifest indicators, and specifying the within-class variance structure. Latent profile models are able to account for different assumptions of the mean and covariance structure of manifest measures. Options include allowing all variances to vary across classes; constraining manifest variable covariance to be equal across classes; fixing within-class variable covariance at zero but allowing variance across classes to be estimated; and fixing within-class covariance of manifest variables to zero and constraining covariance across classes to be equal (but not necessarily at zero). The last two options reflect an assumption of manifest variable independence conditional on class membership (Bauer and Curran 2004; Masyn 2013). These assumptions can impact the number of classes identified, and by extension, the classification of observations into classes. Masyn (2013) recommends specifying various models with these options and selecting a within-class variance structure option based on relative model fit or theoretical and practical considerations.

Model identification proceeds after model specification. It entails comparing the log-likelihood estimates of models with the same number of class solutions but different starting seeds. Models for the same class solution (k=4, for example) that have lower log-likelihood estimates than other models with that same class solution could reflect local maxima of the log-likelihood function. Running a range of models with different starting seeds and selecting the model for each class solution with the highest log-likelihood estimate helps build confidence in the identification of models reflecting the global maximum of the log-likelihood function (Nylund, Asparouhov, and Muthén 2007; Masyn 2013). Only models reflecting the global maxima can be used for subsequent steps. There are no clear recommendations in the literature on the number of classes for which models should be identified. To provide an analytical and conceptual baseline, researchers often start by specifying a model with one class and increase the number of classes by one until model convergence issues are encountered (Nylund-Gibson and Choi 2018).

Once candidate models for each class solution are identified in the model identification step, the class enumeration step can proceed to identify the number of classes present in the data by comparing goodness-of-fit statistics across the range of class solutions. Although there are no universally accepted model fit criteria, there are several broad approaches to determining the number of classes present within the data. These include using information criteria or model criteria. Information criteria are based on statistical analyses of model fit while model criteria evaluate results in light of interpretability and usability (Law and Harrington 2016).

Information criteria include both absolute and relative goodness-of-fit measures. The present analysis will not consider absolute model fit statistics in the class enumeration step, as these are unreliable in latent profile analyses (Masyn 2013). The log-likelihood chi-squared statistic, the most commonly used statistic of absolute model fit in LCA and LPA models, is inaccurate for models with large numbers of manifest variables or variables measured on a continuous measurement scale (Lanza, Bray, and Collins 2012). Commonly used measures of relative model fit include the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) (Nylund, Asparouhov, and Muthén 2007; Stanley, Kellermanns, and Zellweger 2016; Nylund-Gibson and Choi 2018; MacDonald 2018; Petersen, Qualter, and Humphrey 2019). These statistics measure model fit, but penalize for the increased number of classes estimated.

Lower values of AIC and BIC indicate better fit. Since these model fit statistics tend to continually decrease as the number of specified classes increases, they are often plotted and examined for an “elbow” point where the slopes noticeably change. The number of classes associated with this point is often selected as the appropriate number of classes, since increasing the number of classes beyond this number results in diminished returns of model fit (Lanza, Bray, and Collins 2012).

Once the number of classes has been selected, posterior probabilities for class membership are calculated for each observation in the dataset. Posterior classification probabilities range from 0 to 1 and reflect the model-estimated probability of an observation belonging to a particular class in each model (Nylund, Asparouhov, and Muthén 2007).

Analytical Method of Present Study

After extracting all relevant data from IPEDS and the Indiana University Center for Postsecondary Research, I used Stata 15.1 for data merging and all subsequent data management tasks, including allocating parent campus data to child campuses, generating new variables, and dropping non-permitted colleges and universities from the sample. I used the *lclass* option of the *gsem* command in Stata 15.1 (MacDonald 2018; StataCorp 2020) to fit latent profile models to the dataset and predict posterior probabilities of class membership in a manner consistent with the steps of principled model building detailed above. More detail is provided in Chapter 4.

CHAPTER 4: RESULTS

This chapter will provide the results of the analysis, organized by the steps of principled model-building described in the latent profile analysis literature (Nylund, Asparouhov, and Muthén 2007; Lanza, Bray, and Collins 2012; Masyn 2013; Schmiege, Masyn, and Bryan 2017; Porcu and Giambona 2017; Nylund-Gibson and Choi 2018). This includes the steps of model specification, model identification, class enumeration, and classification. A comparison of the results of the latent profile analysis to the 2018 Basic Carnegie Classification are also provided.

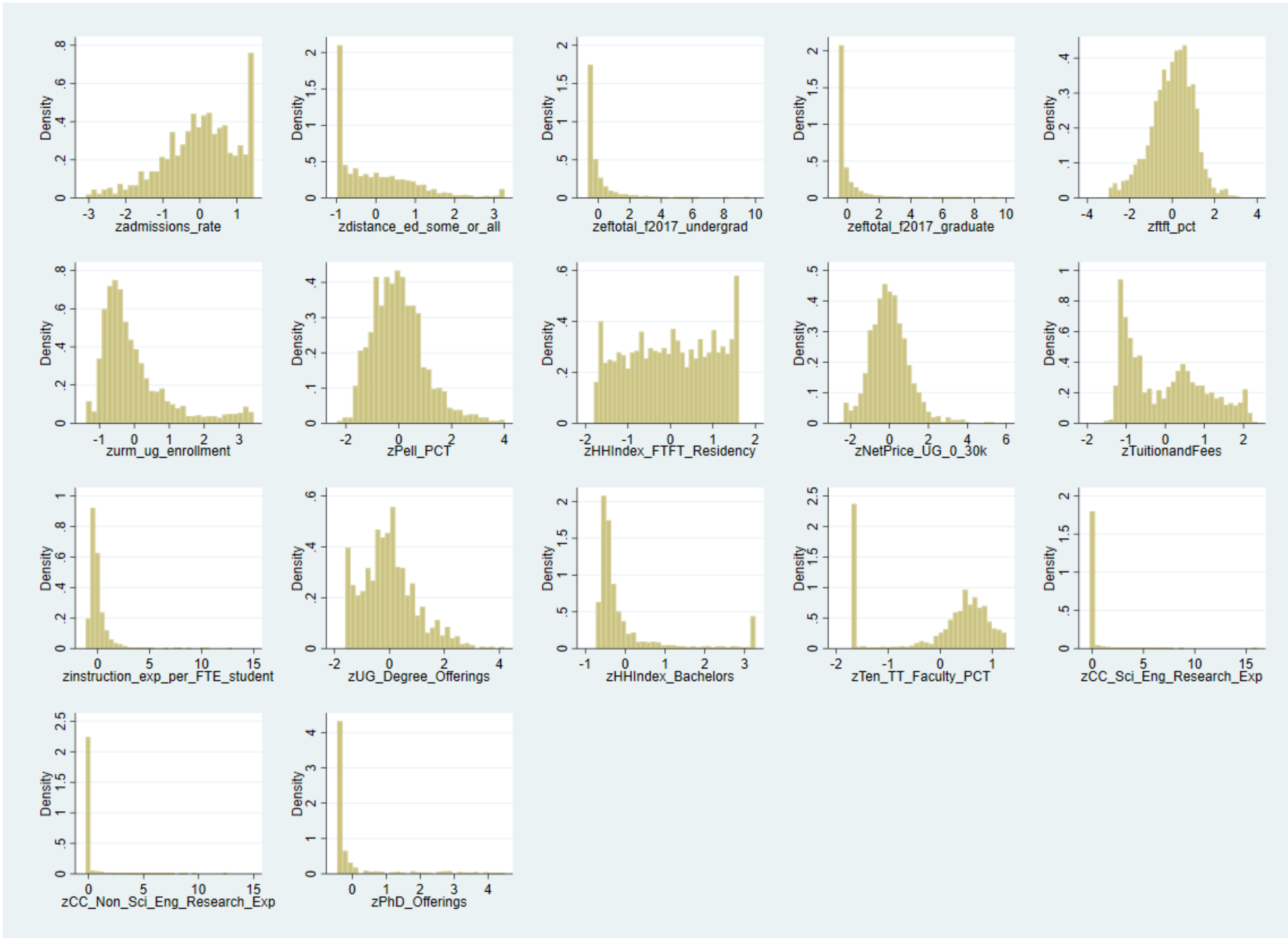
Model Specification

Following convention in the university classification literature, the present study standardized all data with a z-score transformation. Figure 3 provides histograms of the resulting variables. Although inspection of the distributions of manifest variables revealed several non-normal distributions, assumptions of the distributions of manifest variables within classes—rather than in the overall sample—determine the selection of distributions and linking functions in the structural model. The present analysis assumed manifest variables were normally-distributed within classes and used Gaussian distributions within the structural model. Assumptions of within-class variable distributions are required in LPA, although these distributional assumptions are unverifiable because class-membership is not known (Oberski 2016).

Various specifications of the structural model were attempted to accommodate the nonnormally distributed variables, including Poisson, logit, and ordered probit. These models encountered convergence issues or produced uninterpretable classes.

Various specifications of the within-class variance/covariance structures were attempted. Models that did not assume local independence experienced convergence and identification issues and were not able to be estimated and compared.

Figure 3: Histograms of Standardized Variable Transformations



The challenges of fully estimating variance-covariance structures in high-dimensional datasets with latent profile analysis are known (Steinley and Brusco 2011). The present study was only able to consider models that fixed covariance between classes to be equal.

Model Identification

Table 4.1 provides the log-likelihood estimates for models with 1-20 classes with five different start seeds. Following the recommendation of the literature, the model for each class solution that produced the highest log-likelihood estimate was selected for subsequent stages of the analysis. The model selected for each class solution is bolded in Table 3.

Table 3: Log Likelihood Estimates for Classes with Different Starting Seeds

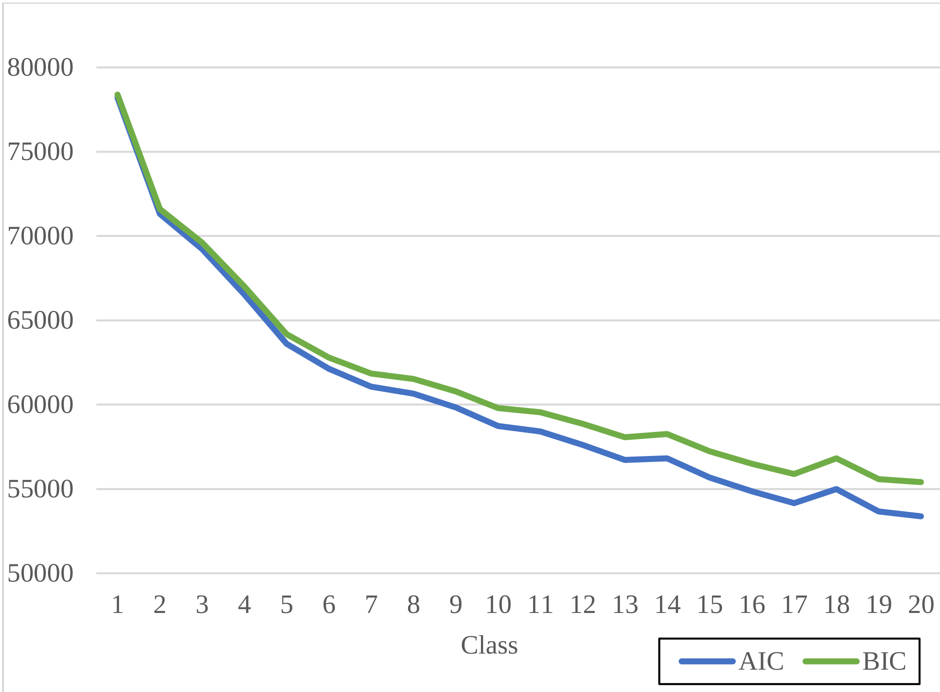
		Starting Seed				
		7	**9**	**11**	**13**	**15**
Class = k	**1**	**-39069.1**	-39069.1	-39069.1	-39069.1	-39069.1
	2	**-35609.5**	-35609.5	-35609.5	-35609.5	-35609.5
	3	-34542	-34542	**-34059.2**	-34542	-34542
	4	**-33024.1**	-33179.1	-33179.1	-33179.1	-33179.1
	5	-31789	-32737.8	-31700.9	**-31696.2**	-32436.1
	6	-31221.7	-31276.8	-30941.5	**-30941.5**	-32330.2
	7	-30959.8	**-30630.5**	-31007.3	-31529.9	-30959.8
	8	-30167.5	-30167.5	-30167.1	-30167.5	**-30167.1**
	9	**-29666.3**	-30023.5	-29790.2	-29754.3	-29735.5
	10	-29420	**-29148.5**	-29174.8	-29420	-29268.7
	11	**-28749.8**	-28776.9	-29026.4	-28887.5	-28987.5
	12	-28653	-28614.7	-28870.4	**-28492.9**	-28535.9
	13	-28612.4	-28151.3	-28151.3	-28390.7	**-28107.6**
	14	-28048.7	-27865	-28161.2	**-27787.3**	-28009.9
	15	-27223	**-27179**	-27222.5	-27542	-27362.1
	16	-27140.4	-27332.2	**-26861**	-27464.3	-26928.1
	17	**-26608.6**	-26838.1	-26837.7	-26634.6	-27077.4
	18	-26681.6	**-26529.1**	-26883.4	-26619.2	-27156.3

19	-26550.8	-27053.7	-26512.3	**-26466.1**	-26548.4
20	**-26284.6**	-26331.7	-26475.9	-26360.4	-26526.6

Class Enumeration

Figure 4 provides goodness-of-fit statistics for the candidate models with classes ranging from 1-20. The elbow in the scree plot at k=5 suggests a 5 class solution. Inspection of these five classes revealed insufficient class homogeneity and class separation for the purpose of creating a classification of colleges and universities. As is common with exploratory techniques, concerns of class interpretability and utility dictated a different number of classes than suggested by only considering model fit statistics (Masyn 2013; Oberski 2016). The 13 class solution was selected on the basis of being the next elbow present within the plot. As such, it is considered the model that balances explanation of the underlying structure of the data with model parsimony and practical utility. The full model output for the 13-class solution is provided in Appendix B.

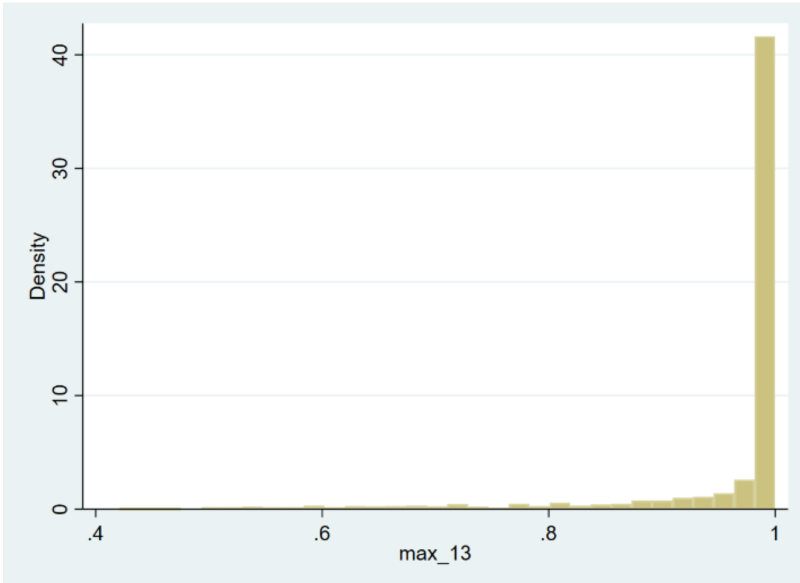
Figure 4: Goodness-of-fit Statistics for Identified Models



Classification

After selecting the number of classes within the dataset, the present study used posterior probabilities to assign all observations to the enumerated classes. Posterior classification probabilities range from 0 to 1 and reflect the model-estimated probability of an observation belonging to a particular class in each model (Nylund, Asparouhov, and Muthén 2007). Observations were assigned to the class for which they had the highest posterior probability. Figure 5 provides a histogram of posterior probabilities of class membership across the observations for the 13-class solution.

Figure 5: Histogram of Posterior Probabilities for Class Membership



The average posterior probability of membership was .959. There were 170 colleges and universities that had posterior probabilities of membership of 1, indicating the highest confidence in class membership. Only three colleges and universities had calculated posterior probabilities less than .5. These were:

Loyola University Chicago (.465)
Medaille College (.451)
Nyack College (.421)

Class Homogeneity

Class homogeneity is critical in evaluating the results from a latent profile analysis as it captures how well the analysis has created homogeneous groupings from the overall sample. It can be evaluated by comparing the within-class variances or standard deviation of variables to these statistics in the overall sample (Masyn 2013). Figure 6 provides the within-class variance for all 17 manifest variables across for each of the 13 derived classes. Since all manifest variables have been standardized, the standard deviation for all variables in the overall sample is one. Thus, Figure 6 shows that all within-class variable standard variations are significantly less than observed in the overall sample. Classes 12 and 6 have the lowest levels of within-class variances across the manifest variables, indicating the highest levels of class homogeneity. Class 11 is the most heterogeneous class, although it is still significantly more homogeneous than the overall sample. The within-class standard deviations observed in Figure 6 are tightly coupled with the size of these classes: Class 12 contains 484 members while Class 4 contains only four members.

Class Separation

Class separation refers to the separation of class-specific variable mean distributions (Masyn 2013). Less overlap between the distributions of class-specific variable means indicates that classes are more separated or "distinct" on a particular variable compared to a variable where more overlap between these distributions is observed. Figure 7 plots the variable mean distributions for each class by variable. Standard normal distributions, which correspond to the distributions of the variable means observed in the overall population, are represented by dotted lines.

The highest-class separation is observed in tuition and fees, Pell-eligible enrollment, and undergraduate degree offerings. The lowest class separation, the most overlap in the distributions of class-specific variables means, is observed in undergraduate enrollment, graduate enrollment, PhD offerings, and instructional expenditures per full-time equivalent student. For each of these variables, however, there are classes where the variable mean distributions are significantly separated from a class group of overlapping mean distributions. This indicates that there is still class separation observed across these variables.

Figure 6: Within-Class Standard Deviation of Manifest Variables by Class

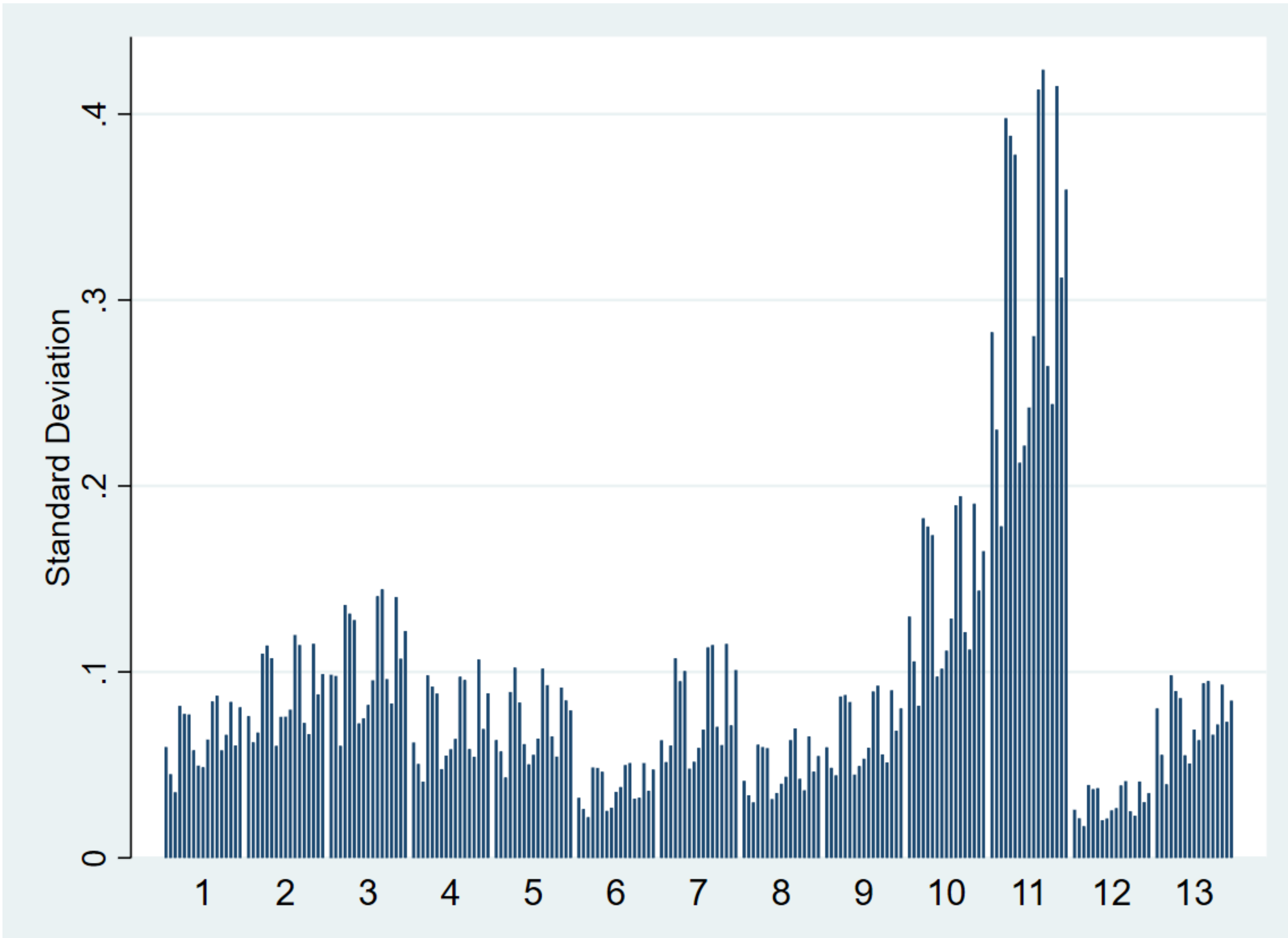


Figure 7: Class-specific Variable Mean Distributions by Variable

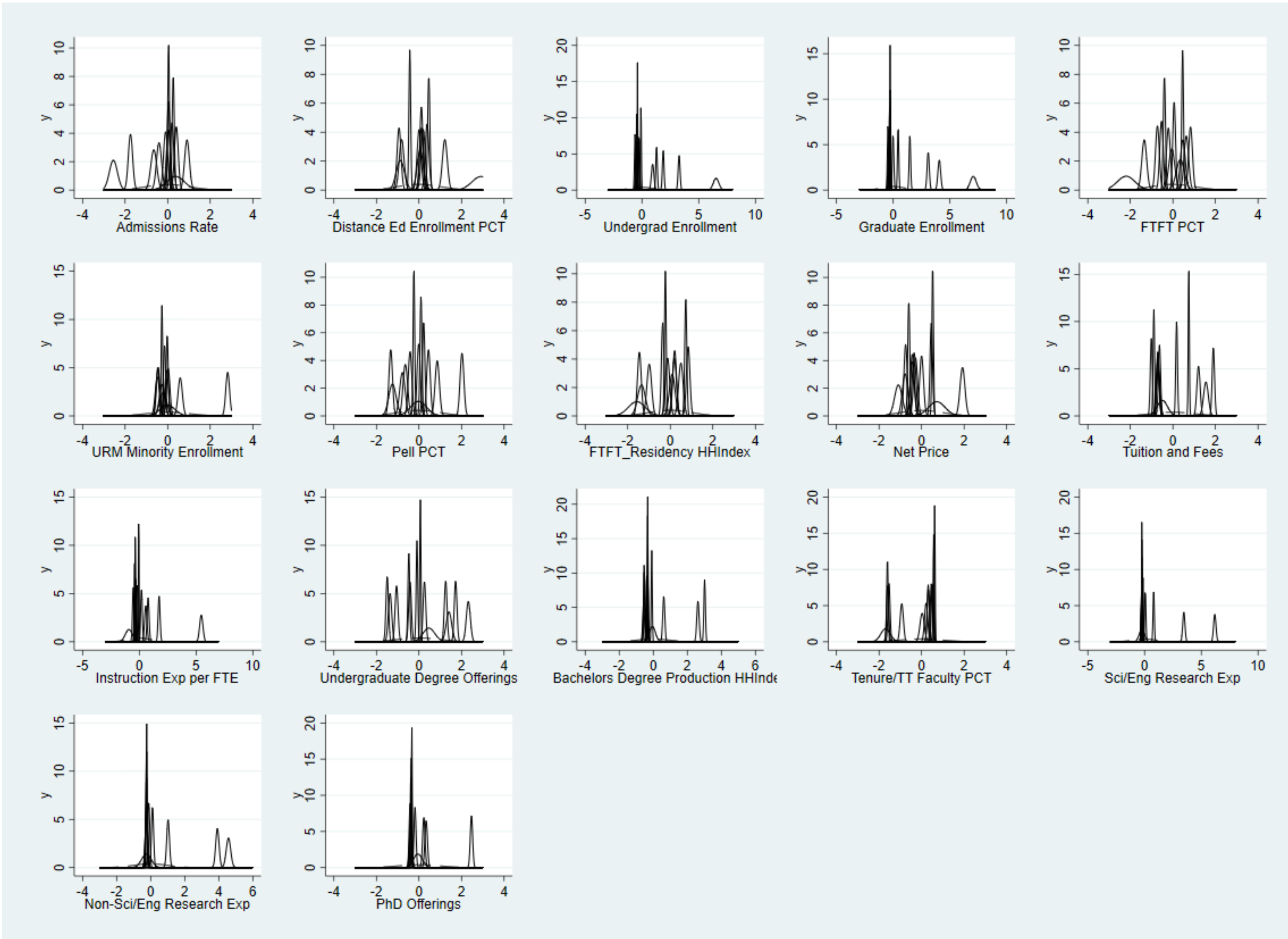


Table 4: Class-specific Variable Means

	Class (k=13)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**Tot.**
Admissions Rate, Percentage	0.73	0.60	0.55	0.66	0.31	0.75	0.89	0.70	0.78	0.14	0.77	0.70	0.70	0.69
Students Enrolled in Distance Education, Percent	0.32	0.04	0.24	0.23	0.01	0.34	0.52	0.26	0.26	0.03	0.92	0.13	0.28	0.23
Undergraduate Enrollment, Count	15992.71	1241.29	32075.31	2766.12	3541.31	4787.88	1791.31	1683.86	516.99	13114.11	58601.00	2215.27	20725.65	5392.66
Graduate Enrollment, Count	2839.55	371.36	10672.66	510.15	1504.39	801.36	706.75	574.66	187.79	13549.58	22400.25	733.47	5914.95	1542.68
FTFT Enrollment, Percent	0.16	0.23	0.20	0.24	0.26	0.17	0.11	0.20	0.15	0.22	0.05	0.23	0.19	0.20
Under-represented Minority Student Enrollment, Percent	0.29	0.18	0.23	0.88	0.19	0.28	0.42	0.26	0.19	0.24	0.28	0.23	0.28	0.29
Pell Grant Enrollment, Percent	36.68	26.76	24.51	68.99	15.77	38.20	50.71	40.36	43.64	17.16	36.50	33.31	30.38	36.84
FTFT Geographic Concentration, HH Index	7872.67	2676.92	5702.89	4993.84	1396.03	7552.37	6910.65	4463.65	6049.46	1674.42	1054.61	4855.04	6036.50	5477.73
Net Price, Dollars	10223.81	29604.15	10036.89	15942.14	12458.17	11134.58	13328.00	19028.21	13060.32	7736.74	20820.00	19366.86	12536.23	15634.10
Tuition and Fees, Dollars	8959.74	40751.29	13744.86	13440.23	50757.74	10341.55	13017.90	26221.82	14558.12	45800.42	16453.00	34222.93	13470.01	23549.24
Instructional Expenditures, Dollars	7533.30	17629.35	15760.89	7550.15	26600.05	7182.74	5456.08	6612.91	8682.06	60889.62	1971.69	9992.86	12167.56	10421.72
Number of Undergraduate Degrees Offered, Count	55.55	5.42	75.40	23.22	36.21	29.70	11.44	22.37	3.13	58.16	40.25	32.54	64.15	31.39
Bachelor's Degree Production, HH Index	1029.15	8483.15	1022.38	1400.60	1547.60	1522.26	3774.73	2079.08	9393.40	1257.29	2185.18	1526.22	1041.76	2301.99
Tenure and Tenure-track Faculty, Percent	0.73	0.26	0.64	0.68	0.74	0.76	0.04	0.03	0.06	0.58	0.00	0.78	0.67	0.57
Science and Engineering Research Expenditures, Dollars	16131.76	1057.73	582344.09	3117.44	47290.24	1074.31	0.00	119.63	0.00	1006841.84	0.00	1268.30	161351.75	37091.55
Non-Science and Engineering Research Expenditures, Dollars	1381.29	23.67	40946.54	204.79	3521.76	72.62	0.00	22.67	0.00	47415.95	0.00	72.34	12539.39	2416.34
PhD Offerings, Count	3.42	0.25	20.00	1.35	4.06	0.45	0.35	0.33	0.15	19.26	2.00	0.54	14.75	2.26

Description of 13 Classes

This section will provide a short description of the distinguishing attributes of each class, listings of representative college and university members, and lists of members that had the lowest calculated posterior probability of membership. Unstandardized class-specific variable means are provided in Table 4.

The number that identifies each class in the section below does not correspond to a hierarchy or rank of any kind. The class numbers are randomly assigned to classes by Stata and are provided here to assist the reader in comparing results as well as subsequent researchers replicating results with the same dataset and Stata syntax.

Class 1: Community-Scale Research Universities

Class 1 colleges and universities are high-access, low-cost, medium-scale colleges and universities that largely serve students from the same state and operate small-scale research enterprises. Class 1 colleges and universities have the highest geographic concentration of FTFT freshman of any class, indicating they enroll mostly students from the state in which they are located. They also have, on average, the lowest tuition and fees of any class and one of the lowest net prices for low-income students. These colleges and universities are comprehensive to the extent that they offer an average of 55 undergraduate degree options, which is the fourth highest across the 13 classes, and degree production is well dispersed across the disciplines. Nearly three-quarters of instructional faculty are tenured or tenure-track. Science and engineering research expenditures per faculty averages $16,131, which ranks 4th highest of any class. The 110

Community-Scale Research Universities identified in the sample enrolled 1,759,198 undergraduates and 312,351 graduate students in 2017-2018. The first 15 members by alphabetical order of Class 1 include:

- Appalachian State University
- Arkansas State University-Main Campus
- Arkansas Tech University
- Ball State University
- Boise State University
- Brigham Young University-Idaho
- California Polytechnic State University-San Luis Obispo
- California State Polytechnic University-Pomona
- California State University-Chico
- California State University-Dominguez Hills
- California State University-East Bay
- California State University-Fresno
- California State University-Fullerton
- California State University-Long Beach
- California State University-Los Angeles

Other representative members of class 1 include:

- Louisiana Tech University
- Northern Arizona University
- Northern Illinois University
- The University of Texas at San Antonio
- San Jose State University
- University of Alaska Anchorage
- University of Maryland-Baltimore County
- University of Wisconsin-Oshkosh
- Western Illinois University
- Utah Valley University

The average maximum posterior classification probability for class 1 colleges and universities was .9301. Table 5 provides the colleges and universities in Class 1 that are least "attached" to this class, as measured by their posterior classification probability, and the class for which they have second highest classification probability.

Table 5: Lowest Posterior Probabilities Observed in Class 1

Institution	Post. Prob. (k=1)	Other Class
Florida Gulf Coast University	0.496476	8
Central Connecticut State University	0.547046	6
University of Minnesota-Duluth	0.565104	6
Western Illinois University	0.605517	6
Kean University	0.607708	6
California State University-Dominguez Hills	0.644361	6
California State University-East Bay	0.675677	6
Texas A & M University-Commerce	0.685495	6
University of North Georgia	0.686252	6

Class 2: Professional Schools

Class 2 colleges are small, professionally oriented colleges that offer degrees in a small number of fields. These college and universities have small student bodies, enrolling an average of 1,241 undergraduates and 371 graduate students. Almost all instruction at class 2 members occurs face-to-face: an average 4% of students are enrolled in some distance education. Although these colleges and universities draw students from across the country, they have the lowest levels of under-represented minority students in their undergraduate student bodies. At an average of $40,751, their average tuition fees ranks fourth highest and the net price for low-income students is the highest of any class. Few low-income students enroll in class 2 colleges. Only 26% of faculty at Class 2 colleges are tenure or tenure-track and colleges have little science and non-science research expenditures. The 55 colleges assigned to Class 2 enrolled a total of 68,271 undergraduates and 20,425 graduate students in 2017-18. The first 15 include:

Albany College of Pharmacy and Health Sciences
Art Center College of Design
Babson College
Bentley University
Berklee College of Music
Bryant University
California Institute of the Arts

Cleveland Institute of Art
Cleveland Institute of Music
College for Creative Studies
College of the Atlantic
Colorado School of Mines
Columbia College Hollywood
Columbus College of Art and Design
Cornish College of the Arts

Other notable examples include:

The Juilliard School
Pratt Institute-Main
Ringling College of Art and Design
Sarah Lawrence College
Rhode Island School of Design

The average posterior probability for colleges belonging to Class 2 is .97. Table 6 provides the ten schools that are least attached to Class 2.

Table 6: Lowest Posterior Probabilities Observed in Class 2

Institution	**Post. Prob. (k=2)**	**Other Class**
Milwaukee School of Engineering	0.596188	8
Pratt Institute-Main	0.702639	12
Montserrat College of Art	0.80917	8
Saint Joseph Seminary College	0.82928	9
Columbia College Hollywood	0.888561	9
John Paul the Great Catholic University	0.90701	9
New Hampshire Institute of Art	0.909532	9
Laguna College of Art and Design	0.938458	9
Columbus College of Art and Design	0.965422	3
Pacific Northwest College of Art	0.986354	9

Class 3: National-Scale Research Universities

Class 3 universities are large, comprehensive, research-intensive universities. Members of Class 3 enroll an average of 32,075 undergraduate students and 10,672 graduate students, the second and third highest of any group, respectively. As a group, tuition and fees and the net price for low-income students are lower than the average observed in the overall sample of colleges and universities. However, the enrollment of Pell-eligible and underrepresented minority students is also less than average in the sample. The enrollment rate of FTFT freshman ranks in the middle of the other classes, indicating that these universities serve a combination of both traditional and non-traditional students.

Class 3 universities are the most comprehensive universities observed in the sample to the extent that they average the highest number of bachelor's and PhD degree offerings. An average of 64% of instructional faculty at these universities are tenure or tenure-track and they average $582,344,000 in science and engineering research expenditures. This is second highest of any class and 3.4 standard deviations above the mean for the sample. The 35 Class 3 universities enrolled 1,122,636 undergraduates and 373,543 graduate students in 2017-18. The first 15 members include:

Arizona State University-Tempe
Boston University
Florida State University
Georgia Institute of Technology-Main Campus
Georgia State University
Indiana University-Bloomington
Michigan State University
Ohio State University-Main Campus
Pennsylvania State University-Main Campus
Purdue University-Main Campus
Rutgers University-New Brunswick
Syracuse University
Texas A & M University-College Station
The University of Texas at Austin
University of Arizona

Other representative members include:

University of California-Berkeley
University of Florida
University of Illinois at Urbana-Champaign
University of Minnesota-Twin Cities
University of South Florida-Main Campus
University of Wisconsin-Madison

Posterior probabilities for membership in Class 3 averages .996 across members. The least-attached members to Class 3 are provided in Table 7.

Table 7: Lowest Posterior Probabilities Observed in Class 3

Institution	Post. Prob. (k=3)	Other Class
University of Colorado Boulder	0.885	13
Syracuse University	0.990	13
University of North Carolina at Chapel Hill	0.997	10
University of Virginia-Main Campus	0.997	13
Washington State University	0.998	13
Georgia State University	0.998	13
University of Iowa	0.999	13

Class 4: Legacy Access Universities

Class 4 schools have small, highly diverse but traditional undergraduate student bodies comprised mostly of students from the local community. Under-represented students comprise an average of 88% of undergraduate enrollment at Class 4 colleges and universities, by far the highest rate of any grouping. They also enroll the highest percentage of Pell-eligible students. Although several other classes have diverse student bodies, Class 4 is unique to the extent that it has one of the highest rates of FTFT freshman enrollment as well as average rates of distance education enrollment. The majority of instructional faculty are tenured and tenure-track, but faculty at these colleges engage in low levels of sponsored research and Ph.D. degree offerings are very limited. Taken together, this indicates Class 4 organizations mostly serve young, traditional learners with traditional learning environments.

Class 4 includes many historically black colleges and universities. There are 81 members in this class and they enrolled 224,056 undergraduates and 41,322 graduate students in 2017-18. The first 15 members include:

Alabama A & M University
Alabama State University
Alcorn State University
Allen University
Benedict College
Bennett College
Bethune-Cookman University
Bloomfield College
Bowie State University
Central State University
Cheyney University of Pennsylvania
Chicago State University
Chowan University
Claflin University
Clark Atlanta University

Other representative members include:

Howard University
Jackson State University
Morehouse College
North Carolina A&T State University
Talladega College
Tuskegee University
University of California-Merced

Posterior probabilities for membership in Class 3 averaged .98. Table 8 provides the colleges and universities that are least attached to Class 4.

Table 8: Lowest Posterior Probabilities Observed in Class 4

Institution	**Post. Prob. (k=4)**	**Other Class**
Nyack College	0.42	12
Lincoln College	0.67	6
Virginia State University	0.69	6
The College of New Rochelle	0.81	12
Southern University at New Orleans	0.82	6
Shaw University	0.87	8
University of North Texas at Dallas	0.94	6
Howard University	0.96	12
Chicago State University	0.98	6
Virginia Union University	0.98	8

Class 5: Classical Academies

Class 5 contains highly selective, high-cost, low-diversity colleges and universities that serve small numbers of undergraduates and graduate students. Class 5 colleges and universities have the second-lowest average admissions rate, the highest combined tuition and fees, and spend the second-highest amount on instruction per student. Their instructional environments are highly traditional: on average, 26% of undergraduates are FTFT freshman and only 1% of students are enrolled in distance education coursework. Three-quarters of instructional faculty at these colleges and universities are tenured or tenure-track. Research expenditures per faculty are above the overall sample average but are still rank significantly below class leaders.

There are 84 colleges and universities assigned to Class 5. Together they enrolled 297,470 undergraduates and 126,369 graduate students in 2017-18. The first 15 members include:

American University
Amherst College
Bard College
Barnard College
Bates College
Boston College
Bowdoin College
Brandeis University
Brown University
Bryn Mawr College
Bucknell University
California Institute of Technology
Carleton College
Carnegie Mellon University
Case Western Reserve University

Other representative members include:

Claremont McKenna College
College of the Holy Cross
College of William and Mary
Dartmouth College
Fordham University
Georgetown University
Princeton University
Swarthmore College
Tufts University

The posterior probabilities of membership across Class 5 colleges and universities average .96. There are several colleges that are only marginally attached to the Class 5, as shown in Table 9. Compared to more strongly attached members of Class 5, these colleges and universities generally have higher admissions rates and lower research intensity.

Table 9: Lowest Posterior Probabilities Observed in Class 5

Institution	**Post. Prob. (k=5)**	**Other Class**
Clark University	0.51	12
Worcester Polytechnic Institute	0.54	2
Santa Clara University	0.63	12
St Olaf College	0.65	12
Stevens Institute of Technology	0.68	12
The University of the South	0.71	12
Earlham College	0.77	12
Case Western Reserve University	0.77	13
Muhlenberg College	0.84	12
Furman University	0.85	12
College of William and Mary	0.85	12

Class 6: Community-Scale Access Colleges

Class 6 contains small-scale, low-cost, medium-access, non-research colleges and universities. On most variables, Class 6 closely tracks the mean values observed across all colleges and universities contained in the sample. They are distinguished by having particularly low tuition and fees, but at the same time, low levels of financial aid: it is one of the few classes where the net price for low-income students exceeds combined tuition and fees. Their undergraduate student bodies also have the second-highest geographic concentration of any class. Class 6 members have minimal research enterprises and few PhD offerings despite having an instructional faculty that is, on average, 76% tenured or tenure-track.

Class 6 has one of the largest memberships of any class. There are 305 colleges and universities assigned to this class and they enrolled 1,460,304 undergraduates and 244,414 graduate students in 2017-18. The first fifteen members include:

Adams State University
Angelo State University
Ashland University
Auburn University at Montgomery
Augusta University
Aurora University
Austin Peay State University
Averett University-Non-Traditional Programs
Bemidji State University
Black Hills State University
Bloomsburg University of Pennsylvania
Bluefield State College
Brescia University
Bridgewater State University
California State University Maritime Academy

Other representative members include:

California State University-Bakersfield
Dickinson State University
Purdue University Fort Wayne
Slippery Rock University of Pennsylvania
University of Wisconsin-Stevens Point

Average maximum posterior probabilities for members of Class 6 average .94. Examination of the least-attached members by class indicates that Class 6 is related to both Class 1 and Class 12, with research intensity being a prime differentiator.

Table 10: Lowest Posterior Probabilities Observed in Class 6

Institution	**Post. Prob. (k=6)**	**Other Class**
CUNY Lehman College	0.50	1
St. Joseph's College-New York	0.51	12
Lee University	0.51	12
Southeast Missouri State University	0.52	1
Michigan Technological University	0.52	1
University of the Cumberlands	0.53	12
Southern Illinois University-Edwardsville	0.55	1
Toccoa Falls College	0.56	12
West Texas A & M University	0.56	1
Carlow University	0.58	12

Campbellsville University	0.58	12

Class 7: Hybrid Professional Academies

Class 7 is comprised of small, non-research, access-oriented colleges and universities that offer a limited number of degree programs largely through digital teaching modalities. Class 7 members average the highest acceptance rate of any class and they enroll the second highest percentage of low-income and under-represented minority students of any class. Only 11% of their undergraduate student bodies are FTFT freshman and 52% are enrolled in at least some distance education, indicating that these colleges largely serve non-traditional learners. These schools offer, on average, just 11 undergraduate degree programs. Many members of Class 7 are affiliated with a religious denomination. There are 80 colleges and universities assigned to Class 7. They collectively enrolled 143,305 undergraduates and 56,540 graduate students in 2017-2018. The first fifteen members include:

American Baptist College
Amridge University
Arlington Baptist University
Baptist Bible College
Baptist University of the Americas
Bellevue University
Bethel University
Beulah Heights University
Boricua College
Brandman University
Calvary University
Cambridge College
Capitol Technology University
Carlos Albizu University-Miami
Central Methodist University-College of Graduate and Extended Studies

Other representative members include:

Brandman University
Divine Word College
Gods Bible School and College
Grace Christian University
Selma University
The Baptist College of Florida

The maximum posterior probabilities for members of Class 7 averages .94. Table 11 lists the members of Class 7 with the lowest posterior probability of class membership.

Table 11: Lowest Posterior Probabilities Observed in Class 7

Institution	**Post. Prob (k=7)**	**Other Class**
Mid-Atlantic Christian University	0.59	8
Randall University	0.60	8
Presentation College	0.67	8
Selma University	0.68	4
Trinity Baptist College	0.72	8
Baptist Bible College	0.73	9
Gwynedd Mercy University	0.74	8
National University	0.77	1
Wilmington University	0.77	8
Beulah Heights University	0.78	9

Class 8: Community-Scale Liberal Arts Colleges

Class 8 is comprised of small, non-research, medium-cost, access-oriented colleges and universities. Class 8 is closely related to Class 7, although Class 8 schools have significantly fewer students enrolled in distance education courses (.26 compared to .52), charge higher tuition and fees ($26,221 compared to $13,017), and enroll lower numbers of low-income and underrepresented minority students. Despite having similar undergraduate and graduate enrollments, Class 8 offers twice as many undergraduate degree programs than Class 7. The 187 colleges and universities classified as Class 8 enrolled 314,882 undergraduates and 107,462 graduates in 2017. The first 15 members include:

Alaska Pacific University
Alice Lloyd College
Albertus Magnus College
Arizona Christian University

Ave Maria University
Azusa Pacific University
Bacone College
Barclay College
Barry University
Bay Path University
Beacon College
Becker College
Bennington College
Bethany Lutheran College
Blue Mountain College

Other representative members include:

College of the Ozarks
Franklin Pierce University
Prescott College
St. Thomas University

The average posterior probabilities of membership for members of Class 8 are .97. Table 12 provides the least-attached members of Class 8.

Table 12: Lowest Posterior Probabilities Observed in Class 8

Institution	**Post. Prob. (k=8)**	**Other Class**
Thomas University	0.50	7
Maharishi University of Management	0.55	7
Pennsylvania State University-Mont Alto	0.60	6
Regis University	0.61	12
Centenary University	0.62	12
Ohio Christian University	0.62	7
Robert Morris University Illinois	0.64	7
William Penn University	0.66	12
Lancaster Bible College	0.70	7
Greensboro College	0.74	12
Southwestern Christian University	0.76	7

Class 9: Seminaries, Yeshivas, and Other Colleges of Divinity

Class 9 colleges are exceptionally small and highly specialized organizations. On average, they enroll just 516 undergraduates and 187 graduate students and offer only 3 different undergraduate degree programs. The vast majority of faculty at Class 9 colleges are not tenured or tenure-track and do not engage in research associated with research expenditures. Class 9 largely includes seminaries, schools of theology, yeshivas, and other types of organizations that prepare students for careers in religious ministry. There are, however, a few number of small colleges specializing in one or two disciplines, such as nursing or mining engineering, that are also included in Class 9. The 91 colleges classified as Class 9 enrolled a total of 47,046 undergraduates and 17,089 in 2017-18. The first 15 members include:

AdventHealth University
American Academy of Art
Apex School of Theology
Appalachian Bible College
Art Academy of Cincinnati
Baptist Memorial College of Health Sciences
Be'er Yaakov Talmudic Seminary
Bellin College
Bet Medrash Gadol Ateret Torah
Boise Bible College
Boston Architectural College
Bryan College of Health Sciences
Central Christian College of the Bible
Central Yeshiva Tomchei Tmimim Lubavitz
Clarkson College

Other representative members include:

Franciscan Missionaries of Our Lady University
Saint Louis Christian College
Hebrew Theological College
Mirrer Yeshiva Cent Institute
Sacred Heart Major Seminary
Sh'or Yoshuv Rabbinical College

The average maximum posterior probability for members of Class 9 is .98. The least-attached members of the class are provided in Table 13.

Table 13: Lowest Posterior Probabilities Observed in Class 9

Institution	**Post. Prob. (k=9)**	**Other Class**
Hebrew Theological College	0.61	7
South Dakota School of Mines and Technology	0.70	6
Oregon College of Art and Craft	0.78	2
American Academy of Art	0.83	2
Criswell College	0.84	7
Logan University	0.89	7

Massachusetts College of Art and Design	0.90	2
Thomas Aquinas College	0.91	2
Nazarene Bible College	0.94	7
Art Academy of Cincinnati	0.95	2

Class 10: High Intensity Research Universities

Class 10 universities are the most highly selective and research-intensive universities in the country. Admitting an average of only 14% of students who apply for undergraduate admissions, the enrollment capacity of Class 10 is the most constrained of any class. These universities also charge the highest average tuition and fees of any class. Although the net price of attendance for low-income students is second-lowest, indicating the presence of generous financial aid policies, Class 10 enrolls the second-lowest percentage of Pell-eligible students. Underrepresented minority enrollment is also the second-lowest of any class. Geographic diversity of members of this class ranks third lowest, meaning that a few states are highly represented in the undergraduate student body. The knowledge enterprise of Class 10 universities is both intensive and comprehensive: science and engineering and non-science research and development expenditures average $1,006,841,000 and $47,415,000, respectively, by far the highest of any class. These universities grant PhD degrees in an average of 19 disciplinary categories, second to only Class 3 National Scale Research Universities.

There are only 19 universities classified as Class 10. These institutions enrolled 249,168 undergraduate and 257,442 graduate in 2017-18. The first 15 members include:

Columbia University in the City of New York
Cornell University
Duke University
Emory University
Harvard University

Johns Hopkins University
Massachusetts Institute of Technology
New York University
Northwestern University
Stanford University
University of California-Los Angeles
University of Chicago
University of Michigan-Ann Arbor
University of Pennsylvania
University of Southern California

Other representative members include:

University of Washington-Seattle Campus
Vanderbilt University
Washington University in St Louis
Yale University

The average maximum posterior probability for members of Class 10 was 1, indicating strong confidence of the model assigning observations to this class. There were no minimally-attached members.

Class 11: National Scale Digital Access Universities

Class 11 is comprised of just four very large universities that are characterized by exceptionally high enrollments of digitally-enrolled students. Over 90% of students at these four universities are enrolled in some or all distance education courses and FTFT enrollment as a percentage of undergraduate enrollment averages only 5%, indicating that these universities largely serve non-traditional learners who attend part-time or are transferring in previously completed college credit to complete a college degree. Instructional expenditures per student average just $1,971, 18.9% of the average for all colleges and universities and 3.2% of highest-ranked class on this measure. Low instructional expenditures at these college likely relates to these universities not having tenured or tenure-track faculty, or any research expenditures as measured by the NSF HERD Survey.

The four members of Class 11 enrolled a total of 234,404 undergraduate and 89,601 graduate students in 2017-18. The members include:

Liberty University
Southern New Hampshire University
University of Maryland-University College
Western Governors University

The average maximum posterior probability for members of Class 10 was 1, indicating strong confidence of the model assigning observations to this class.

Class 12: Legacy Immersion Colleges and Universities

Class 12 colleges and universities are small, access-oriented colleges and universities that serve traditional students on a mostly face-to-face basis. These colleges and universities are distinguished by high admissions rates, high enrollment rates of FTFT freshman students, moderately high tuition and fees, and high percentages of faculty who are tenured and tenure-track. These colleges and universities engage in minimal research. They are closely related to Class 4: Legacy Access Universities, but are distinguished by significantly lower enrollment rates of underrepresented minority students and Pell-eligible students. Containing 484 colleges and universities, Class 12 is the largest class by membership. These organizations enrolled 1,074,408 undergraduates and 355,732 graduate students in 2017-18. The first 15 members include:

Abilene Christian University
Adelphi University
Adrian College
Agnes Scott College
Albion College
Albright College
Alderson Broaddus University
Alfred University
Allegheny College
Alma College
Alvernia University
Alverno College
American International College
American Jewish University
Anderson University

Other representative members include:

Berea College
Biola University
California Lutheran University
Drake University
Embry-Riddle Aeronautical University-Prescott
Hampden-Sydney College
Lewis & Clark College
Marquette University

The average maximum posterior probability for members of Class 12 was .96. Many of the marginally attached members of Class 6 charge tuition and fees lower than the class average.

Table 14: Lowest Posterior Probabilities Observed in Class 12

Institution	Post. Prob. (k=12)	Other Class
Medaille College	0.45	6
University of Providence	0.52	6
Saint Peter's University	0.52	4
Chaminade University of Honolulu	0.53	6
Tennessee Wesleyan University	0.55	6
Pennsylvania State University-Altoona	0.56	6
Yeshiva University	0.58	5
Concordia University Texas	0.58	6
Kuyper College	0.59	6
Indiana Institute of Technology	0.59	6

Class 13: Regional-Scale Research Universities

Class 13 colleges and universities are medium-scale comprehensive research universities. These universities closely resemble Class 3 National-Scale Research Universities but are distinguished by smaller undergraduate and graduate enrollments and lower research expenditures. Although their science and engineering research expenditures average approximately a one-quarter that of Class 3 members, this class still ranks third highest on this metric. Class 13 universities offer, on average, 64 different undergraduate degree offerings and grant PhD degrees in 14 disciplinary categories, ranking 2nd and 3rd highest of any class. There are 84 universities classified in Class 13. In aggregate, they enrolled 1,740,955 undergraduate and 496,856 graduate students in 2017-18. The first 15 members include:

Auburn University
Baylor University
Binghamton University
Bowling Green State University-Main Campus
Brigham Young University-Provo
Clemson University
Colorado State University-Fort Collins
Drexel University
Florida Atlantic University
Florida International University
George Mason University
George Washington University
Indiana University-Purdue University-Indianapolis
Iowa State University
Kansas State University

Other representative universities include:

Texas Tech University
Oregon State University
University of Louisville
University of California-Riverside
University of Connecticut
The University of Texas at El Paso
University of New Mexico-Main Campus
Wayne State University

The average maximum posterior probability for members of Class 10 was .98.

Table 15: Lowest Posterior Probabilities Observed in Class 13

Institution	**Post. Prob. (k=13)**	**Other Class**
Loyola University Chicago	0.46	12
Texas Tech University	0.77	3
The University of Texas at El Paso	0.77	1
Texas State University	0.81	1
University of Vermont	0.81	1
Florida Atlantic University	0.82	1
Nova Southeastern University	0.85	8
New Mexico State University-Main Campus	0.97	1
University of Nevada-Reno	0.98	1

Western Michigan University	0.99	1

Comparison of LPA results to 2018 Basic Carnegie Classification

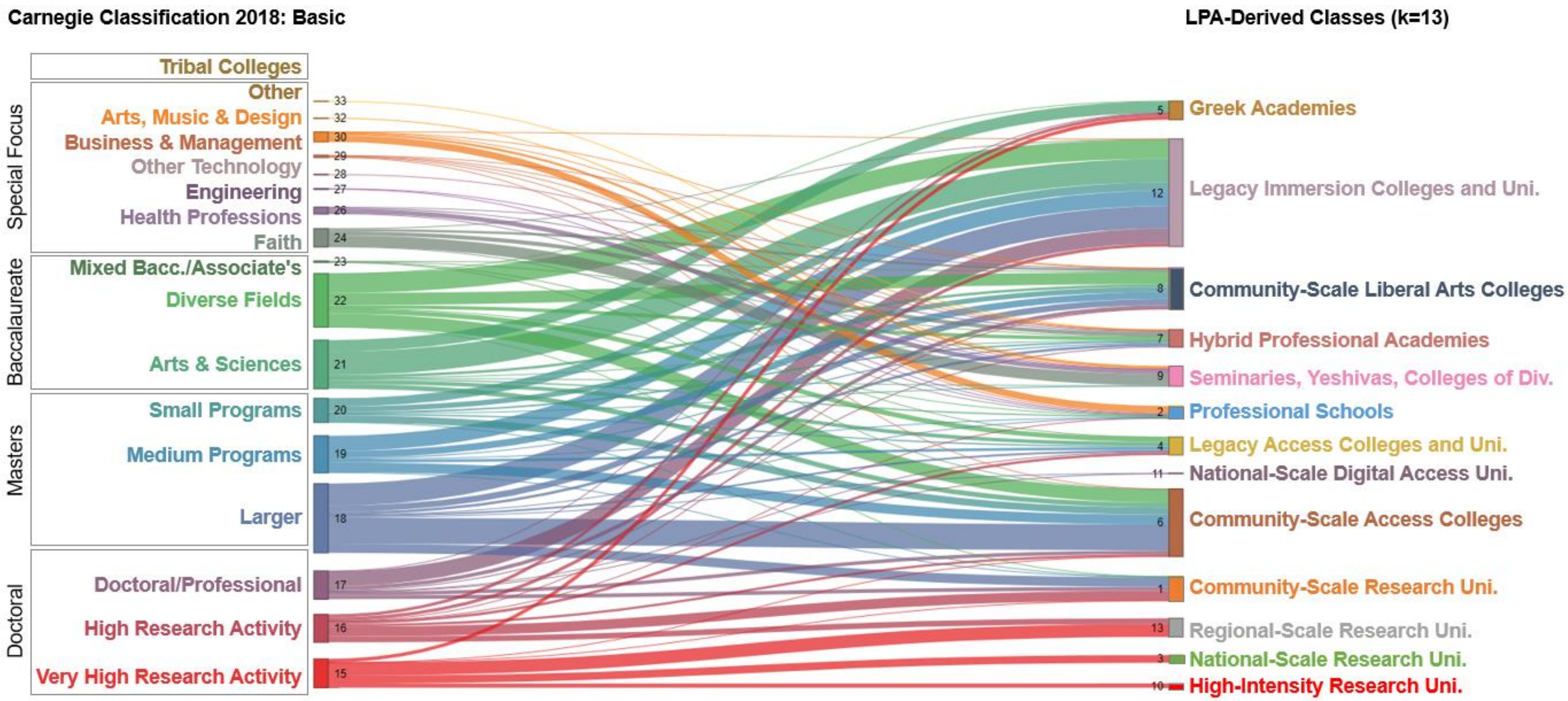
There are 17 classes of the 2018 Basic Carnegie Classification represented in the sample used for the present analysis. Table 16 tabulates the relationship of classifications of the k=13 latent profile analysis solution against the 2018 Basic Carnegie Classification. Figure 8 presents these tabulations graphically with a Sankey diagram.

While there are some correlations between class assignments across these two classifications, there are many noticeable differences. For example, the 130 colleges and universities in the sample that Carnegie classifies as Very High Research Activity Doctoral Universities—also called “R1”—split between six different classes of the latent profile analysis. The LPA-derived classes that these R1 colleges and universities split into are also populated by institutions that Carnegie classifies as Doctoral Universities, Master’s Colleges and Universities, and Baccalaureate Colleges.

Table 16: Classification Comparison between 2018 Carnegie Classification and LPA Results

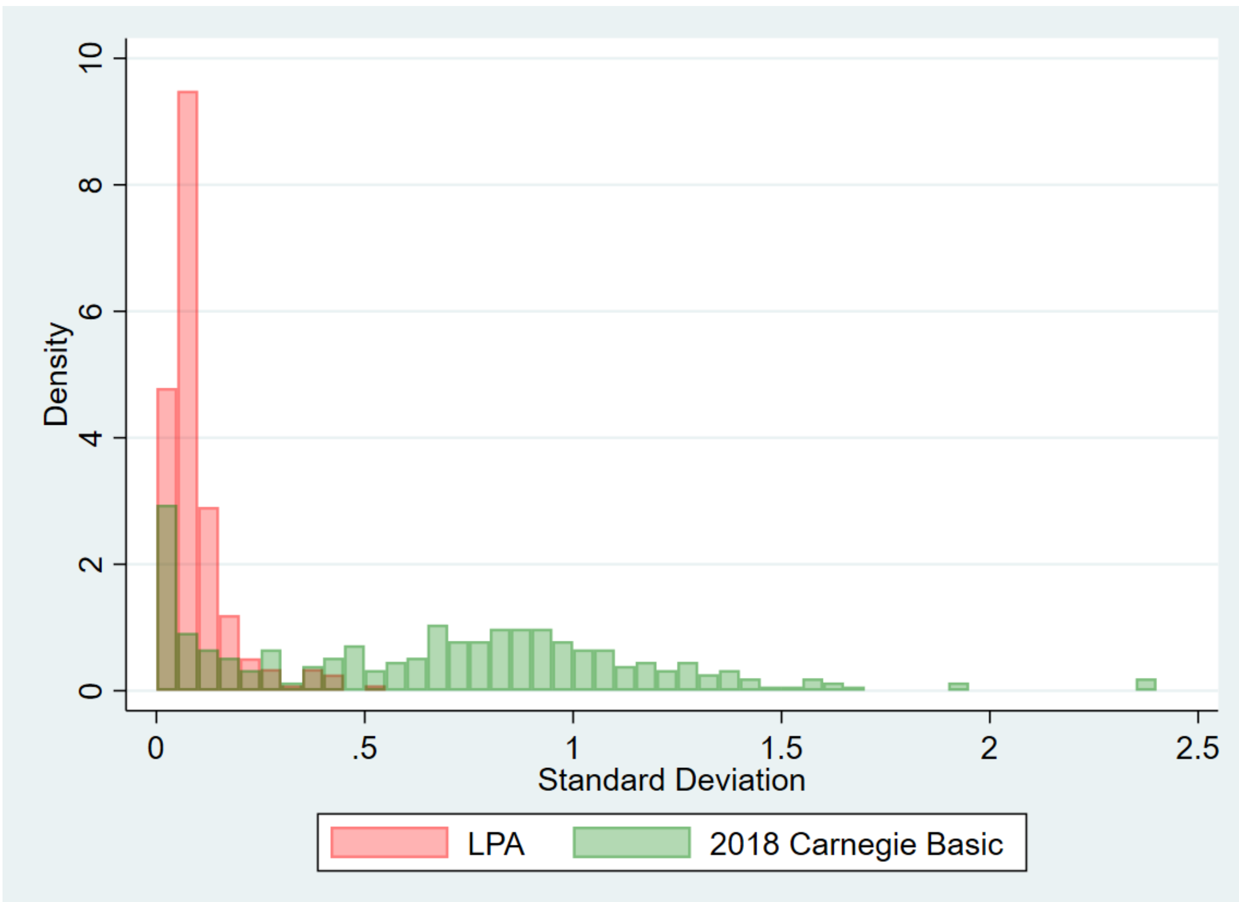
	LPA –Derived Classes (k=13)													
Carnegie Classification 2018: Basic	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**Total**
Doctoral Universities: Very High Research Activity	1	0	35	0	16	1	0	0	0	19	0	0	58	**130**
Doctoral Universities: High Research Activity	45	1	0	12	14	11	0	2	0	0	0	15	26	**126**
Doctoral/Professional Universities	17	0	0	2	1	16	5	17	0	0	1	68	0	**127**
Master's Colleges & Universities: Larger Programs	42	1	0	9	0	117	12	28	0	0	3	100	0	**312**
Master's Colleges & Universities: Medium Programs	3	3	0	12	0	44	5	31	0	0	0	69	0	**167**
Master's Colleges & Universities: Small Programs	1	0	0	6	0	32	8	23	1	0	0	38	0	**109**
Baccalaureate Colleges: Arts & Sciences Focus	0	6	0	17	52	22	1	12	3	0	0	106	0	**219**
Baccalaureate Colleges: Diverse Fields	1	1	0	22	1	60	16	54	0	0	0	87	0	**242**
Baccalaureate/Associate's Colleges: Mixed Bacc./Associate's	0	0	0	1	0	1	2	3	0	0	0	0	0	**7**
Special Focus Four-Year: Faith-Related Institutions	0	2	0	0	0	0	18	11	51	0	0	1	0	**83**
Special Focus Four-Year: Other Health Professions Schools	0	4	0	0	0	0	5	2	21	0	0	0	0	**32**
Special Focus Four-Year: Engineering Schools	0	3	0	0	0	0	0	0	1	0	0	0	0	**4**
Special Focus Four-Year: Other Technology-Related Schools	0	0	0	0	0	0	3	0	0	0	0	0	0	**3**
Special Focus Four-Year: Business & Management Schools	0	3	0	0	0	1	2	2	2	0	0	0	0	**10**
Special Focus Four-Year: Arts, Music & Design Schools	0	31	0	0	0	0	1	2	10	0	0	1	0	**45**
Special Focus Four-Year: Other Special Focus Institutions	0	0	0	0	0	0	0	0	2	0	0	0	0	**2**
Tribal Colleges	0	0	0	0	0	0	2	0	0	0	0	0	0	**2**
Total	**110**	**55**	**35**	**81**	**84**	**305**	**80**	**187**	**91**	**19**	**4**	**485**	**84**	**1,620**

Figure 8: Sankey Diagram Comparison between 2018 Carnegie Classification and LPA Results



Relative class homogeneity in the LPA and Carnegie Classifications can be compared by examining the distributions of class-specific variable standard deviations in the two classifications. Figure 9 plots these values. Since all variables have been standardized, standard deviations can be compared across variables and classifications in this manner.

Figure 9: Histograms for Class-Specific Variable Standard Deviations by Classification



The class-specific variable standard deviations in the LPA model are considerably lower than the class-specific variable standard deviations in the 2018 Basic Carnegie Classification. This indicates that the classes latent profile analysis creates are considerably more homogeneous with respect to the 17 variables used in it. This is particularly interesting given that the LPA results presented here have four fewer classes than the 2018 Carnegie Classification. Additional research is needed to compare the relative class homogeneity on other measures of university behaviors and outcomes, such as graduation rates or degree production efficiency.

CHAPTER 5: DISCUSSION

Colleges and universities are one of the most diverse sets of organizations that exist. Formal classifications, which attempt to create groupings of organizations based on similarities across one or more attributes of interest, are a key way the field uses to understand and manage the complexity of organizational forms encountered. These homogeneous groupings of colleges and universities serve a variety of more specific purposes, such as assisting researchers investigating phenomena occurring in these organizations by providing sample frames or the ability to account for unobserved organizational characteristics within empirical models. These groupings also assist political principals and organizational leaders in assessing organizational performance.

The development of theories and methods for separating colleges and universities into homogeneous groups and the assignment of organizations into these groups has been the subject of extensive applied work (Indiana University Center for Postsecondary Research 2019; McCormick and Zhao 2005) and a small academic literature (Brint, Riddle, and Hanneman 2006; Harmon et al. 2019; Kosar and Scott 2018; Crisp et al. 2019).

This study contributes to the literature in several ways. First, it grounds the differentiation of organizations in the theory of realized publicness in order to create a classification based on the ways in which colleges and universities engage in behaviors that realize public values. It does not incorporate measures of the outcomes of these behaviors. In this way, the present study explicitly separates organizational classification from organizational performance assessment. Second, this study engages the full complexity of the higher education field to create a broad classification of types rather than a classification of a small, pre-defined subset of colleges and universities. The study created a classification from the analysis 17 variables across 1,620 colleges and universities—1,000 observations more than other recently published university classifications. Third, it introduces a new analytical method, latent profile analysis (LPA), to the classification of colleges and universities and describes the steps of principled model-building within this context.

Latent Profile Analysis of College and University Data

To summarize the findings relative to the research questions of the present study, the analysis finds 13 distinct, identifiable organizational designs present in the sample of four-year colleges and universities in the United States. Using posterior probabilities of membership, this analysis finds that membership in these classes range from 4 members to 484 members. Inspection of these probabilities, as well as class-specific variable means, reveals the relationships among these classes.

The LPA produced groupings of colleges and universities significantly more homogeneous than Carnegie's 2018 Basic Classification classes. Even though colleges and universities in the sample represented 17 classes in the 2018 Basic Classification—four more than the LPA-derived solution—the class-specific variable standard deviations within the 2018 Carnegie Classification were significantly higher than in the LPA-derived classes.

Limitations and Future Directions

In exploratory uses of LPA, the true number of classes present within a population is not known *a priori*. Limitations to the method in general, as well as the specific use of the method in the present study, may have resulted in the identification of spurious classes or the under-extraction of classes. Future work can investigate the nature and consequences of these possible issues.

First, future work can investigate alternative specifications of the structural model. This includes employing other family and link functions, as appropriate, to accommodate non-normal distributions of the manifest variables. Relative fit statistics from competing specifications can be assessed to determine if alternative model specifications better explain the data (Masyn 2013; Canette 2018; MacDonald 2018).

Second, future work can investigate alternative specifications of the within-class variance structure. The model presented here assumed local interdependence of manifest variables. Although latent profile models do not need conditional interdependence to estimate models, specification of the within-class variance structure can impact the number and composition of classes predicted by the models (Bauer and Curran 2004). The present study attempted to relax assumptions about the within-class variance structures, but these models quickly encountered convergence and identification issues. If future work is not able to overcome the significant computational challenges in estimating these models, research could examine models with fewer manifest variables or consolidate variables by using metavariables or principal components (McLachlan 2011). While these choices may assist software packages in better estimating computationally intensive models, it is also possible that these choices could reduce the ability of the model to form interpretable groups.

Third, future work could investigate the inclusion of different manifest variables. LPA assumes that the presence of homogeneous subpopulations can explain the heterogeneity observed within the manifest variables. The heterogeneity observed across the manifest variables, however, may be due to other phenomena beside membership in classes. Incorporating different manifest variables or covariates in subsequent research, as well as using derived latent classes in latent class regressions may help illuminate the nature of this potential issue.

Beyond model specification issues, there are exciting possibilities to extend the analysis to an even broader sample of the higher education field. Future research could expand the analysis to include for-profit colleges and universities. Since these organizations report on different accounting standards (National Center for Education Statistics 2020a), possible analytical strategies include analyzing for-profit institutions separately as a group or finding ways to create a fully harmonized dataset so that for-profit organizations can be analyzed alongside public and private not-for-profit organizations. Creating a unified sample of public, private not-for-profit, and private for-profit organizations would likely cause the classes identified here to consolidate into fewer classes with more observations.

Subsequent investigations could put this methodological approach in motion over time. LPA is cross-sectional in nature, meaning that it derives groups and classifies observations into classes based on data captured at one point in time. Latent transition analysis (LTA), on the other hand, considers the presence of group membership within a population through time (Collins and Lanza 2009). This method allows researchers to fix or vary the number of classes estimated across time periods. It may be particularly interesting to examine the stability and emergence of college and university classes through time. An LTA would present data difficulties, however, as IPEDS data availability on my variables becomes a major concern in the years before 2000.

Conclusion

The present study has shown that latent profile analysis can be used to create groupings of colleges and universities that are more homogeneous than the prevailing classification scheme in higher education. The ultimate success of any classification, however, is not entirely dependent on its ability to create homogeneous groupings of observations. There are important additional considerations in the classification of colleges and universities.

There may be practical reasons that dictate the classification of colleges and universities with certain attributes. This analysis did not exclude or otherwise differentially treat organizations belonging to any recognized group or alliance, such as tribal colleges, historically Black colleges and universities, or Hispanic-serving institutions; university sports leagues; or geographic regions within the United States.

The simultaneous analytical consideration of all colleges and universities may or may not be desirable in the context of a higher education classification scheme. If a subset of certain organizations were removed from the sample and "forced" together in a class before conducting a latent profile analysis, their omission from the sample would likely affect both the number and characteristics of classes identified within the remaining sample.

Given that academic researchers and practitioners often collapse the 27 sub-classes of the Carnegie Basic Classification into broader classes, it is likely that practitioners and users of classifications may desire a classification with a small number of classes. The number of classes may also be a critical consideration for developers of classifications who are interested in ensuring interpretability of the classification itself. Research has shown that humans can hold 7+/-2 objects in short-term memory (G. A. Miller 1956), indicating there may be practical considerations for advancing a classification scheme with fewer than nine classes. Masyn (2013) notes that substantive and theoretical knowledge can help practitioners decide on the utility of specific classes when the number of classes dictated by practical parsimony is fewer than the number of classes suggested by relative measures of model fit. There is, of course, a tradeoff between the number of classes and the utility of those classes: the fewer the number of classes for observations to be classified into, the more heterogeneity will be observed within them and the less likely they will have clear, interpretable profiles.

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APPENDIX A

APPENDIX TABLE: 2018 BASIC CLASSIFICATION DESCRIPTIVE STATISTICS

Appendix Table: 2018 Basic Classification Descriptive Statistics

	n	Total Undergrad Enrollment, 2017	Total Graduate Enrollment, 2017	Avg. Undergrad Enrollment, 2017	Average Graduate Enrollment, 2017
Associate's Colleges: High Transfer-High Traditional	122	1,621,743	0	13,293	0
Associate's Colleges: High Transfer-Mixed Traditional/Nontraditional	118	1,642,224	0	13,917	0
Associate's Colleges: High Transfer-High Nontraditional	82	717,312	0	8,748	0
Associate's Colleges: Mixed Transfer/Vocational & Technical-High Traditional	123	1,244,859	8	10,121	0
Associate's Colleges: Mixed Transfer/Vocational & Technical-Mixed Traditional/Nontraditional	106	1,026,254	0	9,682	0
Associate's Colleges: Mixed Transfer/Vocational & Technical-High Nontraditional	111	925,732	0	8,416	0
Associate's Colleges: High Vocational & Technical-High Traditional	138	461,234	0	3,575	0
Associate's Colleges: High Vocational & Technical-Mixed Traditional/Nontraditional	97	434,773	0	4,675	0
Associate's Colleges: High Vocational &	101	553,195	0	5,645	0

Technical-High Nontraditional					
Special Focus Two-Year: Health Professions	262	196,337	0	779	0
Special Focus Two-Year: Technical Professions	65	51,361	0	815	0
Special Focus Two-Year: Arts & Design	30	8,050	0	278	0
Special Focus Two-Year: Other Fields	66	29,000	0	483	0
Baccalaureate/Associate's Colleges: Associate's Dominant	111	1,284,297	148	11,675	1
Doctoral Universities: Very High Research Activity	131	3,043,419	1,251,059	23,232	9550
Doctoral Universities: High Research Activity	135	1,726,450	540,154	13,179	4001
Doctoral/Professional Universities	152	1,232,394	701860	8,216	4618
Master's Colleges & Universities: Larger Programs	350	2,967,096	820163	8575	2343
Master's Colleges & Universities: Medium Programs	196	648309	118459	3359	604
Master's Colleges & Universities: Small Programs	139	366522	60647	2675	436
Baccalaureate Colleges: Arts & Sciences Focus	240	394962	23922	1653	100
Baccalaureate Colleges: Diverse Fields	330	624581	25751	1934	78
Baccalaureate/Associate's Colleges: Mixed Baccalaureate/Associate's	151	557713	4721	3873	31

Special Focus Four-Year: Faith-Related Institutions	300	48661	57843	253	193
Special Focus Four-Year: Medical Schools & Centers	56	15966	114858	726	2051
Special Focus Four-Year: Other Health Professions Schools	259	201859	104490	1062	403
Special Focus Four-Year: Engineering Schools	7	10423	1656	1737	237
Special Focus Four-Year: Other Technology-Related Schools	13	23560	6898	1963	531
Special Focus Four-Year: Business & Management Schools	75	89218	32730	1394	436
Special Focus Four-Year: Arts, Music & Design Schools	118	112384	15266	1031	129
Special Focus Four-Year: Law Schools	35	41	20424	41	584
Special Focus Four-Year: Other Special Focus Institutions	36	14072	19719	612	548
Tribal Colleges	34	24076	257	708	8
Not in Carnegie universe (not accredited or non-degree-granting)	2568	677718	5397	292	2
Grand Total		**22975795**	**3926430**	**3669.1**	**572.6**

APPENDIX B

APPENDIX TABLE: LPA MODEL OUTPUT

Appendix Table: LPA Model Output

	Coef.	Var.	95% CI	
Constant				
1b.A	0	0	0	0
2.A	-0.69954	0.031177	-1.04561	-0.35347
3.A	-1.14954	0.040819	-1.54553	-0.75356
4.A	-0.285	0.025219	-0.59626	0.026251
5.A	-0.2812	0.025793	-0.59597	0.033578
6.A	1.023002	0.01716	0.766253	1.279752
7.A	-0.32578	0.027233	-0.64922	-0.00235
8.A	0.522922	0.017831	0.261201	0.784644
9.A	-0.20276	0.023522	-0.50335	0.09784
10.A	-1.76346	0.064314	-2.26051	-1.26641
11.A	-3.32176	0.26168	-4.32437	-2.31915
12.A	1.464842	0.014124	1.231916	1.697769
13.A	-0.28194	0.024373	-0.58793	0.024052
Admissions Rate, Percentage				
1.A	0.204812	0.007072	0.039994	0.36963
2.A	-0.40512	0.01434	-0.63983	-0.17041
3.A	-0.65063	0.019799	-0.92641	-0.37485
4.A	-0.09617	0.009488	-0.28709	0.09474
5.A	-1.74665	0.01035	-1.94605	-1.54725
6.A	0.262655	0.002484	0.164981	0.360329
7.A	0.909301	0.012799	0.687569	1.131034
8.A	0.040157	0.004002	-0.08383	0.16414
9.A	0.409091	0.007994	0.233848	0.584333
10.A	-2.55054	0.035936	-2.92209	-2.17899
11.A	0.37567	0.170714	-0.43414	1.185479
12.A	0.045749	0.001515	-0.03055	0.122046
13.A	0.040252	0.008816	-0.14378	0.224281
Students Enrolled in Distance Education, Percent				
1.A	0.384437	0.007602	0.213546	0.555328
2.A	-0.814	0.013082	-1.03818	-0.58983
3.A	0.057946	0.020863	-0.22515	0.341047
4.A	0.006748	0.00915	-0.18074	0.194233
5.A	-0.93633	0.00862	-1.1183	-0.75436

6.A	0.462642	0.002594	0.362828	0.562456
7.A	1.216698	0.013089	0.992463	1.440933
8.A	0.113737	0.004844	-0.02268	0.250152
9.A	0.124694	0.008561	-0.05665	0.306038
10.A	-0.874	0.037804	-1.25508	-0.49292
11.A	2.916808	0.179591	2.08621	3.747405
12.A	-0.43022	0.001696	-0.51092	-0.34951
13.A	0.199498	0.009047	0.01307	0.385926

Undergraduate Enrollment, Count

1.A	1.291478	0.004375	1.161836	1.421119
2.A	-0.50804	0.004431	-0.6385	-0.37758
3.A	3.278032	0.006895	3.115287	3.440777
4.A	-0.31994	0.002956	-0.4265	-0.21339
5.A	-0.22683	0.002963	-0.33352	-0.12015
6.A	-0.0805	0.001048	-0.14394	-0.01707
7.A	-0.45362	0.003671	-0.57237	-0.33487
8.A	-0.45046	0.001317	-0.52159	-0.37932
9.A	-0.59965	0.002636	-0.70027	-0.49903
10.A	0.948523	0.012541	0.729031	1.168015
11.A	6.535326	0.059555	6.057017	7.013635
12.A	-0.38817	0.000512	-0.43253	-0.3438
13.A	1.877588	0.005135	1.737142	2.018034

Graduate Enrollment, Count

1.A	0.435401	0.003337	0.322176	0.548625
2.A	-0.39053	0.005261	-0.53269	-0.24837
3.A	3.082667	0.009224	2.894428	3.270906
4.A	-0.34403	0.003424	-0.45872	-0.22934
5.A	-0.01433	0.004264	-0.14231	0.113653
6.A	-0.25448	0.001013	-0.31687	-0.19208
7.A	-0.29859	0.00496	-0.43663	-0.16056
8.A	-0.32288	0.001804	-0.40612	-0.23964
9.A	-0.45862	0.003094	-0.56765	-0.3496
10.A	4.059969	0.014733	3.822069	4.297869
11.A	7.052878	0.069931	6.534576	7.571179
12.A	-0.26909	0.000625	-0.3181	-0.22008
13.A	1.468698	0.004376	1.339044	1.598353

FTFT Enrollment, Percent

1.A	-0.53606	0.007028	-0.70037	-0.37175
2.A	0.468269	0.013239	0.242753	0.693786
3.A	-0.05256	0.019651	-0.32731	0.222195
4.A	0.631939	0.011378	0.422875	0.841004
5.A	0.828648	0.008387	0.649159	1.008138
6.A	-0.40001	0.00259	-0.49975	-0.30027
7.A	-1.34513	0.013224	-1.57052	-1.11975
8.A	0.059667	0.004264	-0.06832	0.187652
9.A	-0.72771	0.008107	-0.90418	-0.55124
10.A	0.348564	0.03626	-0.02465	0.72178
11.A	-2.19611	0.17226	-3.00958	-1.38264
12.A	0.456548	0.001684	0.37612	0.536976
13.A	-0.21123	0.008668	-0.39371	-0.02876

Under-represented Minority Student Enrollment, Percent

1.A	0.026276	0.006548	-0.13232	0.184873
2.A	-0.48462	0.009759	-0.67825	-0.291
3.A	-0.26618	0.014866	-0.50515	-0.02721
4.A	2.821221	0.007823	2.647862	2.994579
5.A	-0.44713	0.00628	-0.60245	-0.29181
6.A	-0.02132	0.002253	-0.11435	0.071715
7.A	0.590436	0.010181	0.392674	0.788197
8.A	-0.1463	0.002991	-0.25349	-0.0391
9.A	-0.46163	0.006451	-0.61906	-0.30421
10.A	-0.21074	0.027177	-0.53385	0.112366
11.A	-0.01574	0.12911	-0.71999	0.688512
12.A	-0.26784	0.001207	-0.33593	-0.19975
13.A	-0.04361	0.007143	-0.20926	0.122036

Pell Grant Enrollment, Percent

1.A	-0.01345	0.005938	-0.16448	0.137574
2.A	-0.64217	0.011534	-0.85266	-0.43168
3.A	-0.77833	0.016338	-1.02885	-0.52781
4.A	2.022212	0.007797	1.849152	2.195273
5.A	-1.3273	0.00697	-1.49093	-1.16367
6.A	0.095207	0.002143	0.004477	0.185937
7.A	0.859031	0.010081	0.662239	1.055824
8.A	0.219138	0.003468	0.103722	0.334554
9.A	0.44812	0.007014	0.283977	0.612263
10.A	-1.24717	0.030094	-1.58718	-0.90716

11.A	-0.02174	0.142964	-0.76281	0.719335
12.A	-0.23818	0.001406	-0.31167	-0.16469
13.A	-0.41772	0.007366	-0.58594	-0.2495
FTFT Geographic Concentration, HH Index				
1.A	0.8409	0.006667	0.680864	1.000936
2.A	-0.98805	0.012056	-1.20326	-0.77285
3.A	0.090954	0.018493	-0.17558	0.357487
4.A	-0.12442	0.009629	-0.31674	0.067904
5.A	-1.45241	0.007948	-1.62714	-1.27768
6.A	0.727641	0.002354	0.632554	0.822727
7.A	0.49937	0.011522	0.288989	0.709751
8.A	-0.35422	0.003702	-0.47347	-0.23497
9.A	0.205609	0.007527	0.03557	0.375649
10.A	-1.35293	0.033333	-1.71076	-0.99509
11.A	-1.57382	0.15817	-2.35331	-0.79433
12.A	-0.23107	0.001536	-0.30788	-0.15425
13.A	0.19205	0.009627	-0.00026	0.384361
Net Price, Dollars				
1.A	-0.75026	0.00598	-0.90182	-0.59869
2.A	1.922908	0.013038	1.699116	2.146701
3.A	-0.77227	0.017247	-1.02967	-0.51488
4.A	-0.00114	0.008476	-0.18159	0.179308
5.A	-0.43692	0.010464	-0.63741	-0.23642
6.A	-0.60046	0.002336	-0.69518	-0.50573
7.A	-0.28409	0.009014	-0.47017	-0.09801
8.A	0.45677	0.003538	0.340187	0.573352
9.A	-0.35259	0.007658	-0.5241	-0.18108
10.A	-1.08938	0.031744	-1.43859	-0.74018
11.A	0.715308	0.150796	-0.04579	1.47641
12.A	0.521261	0.001364	0.448868	0.593653
13.A	-0.43959	0.008044	-0.61538	-0.2638
Tuition and Fees, Dollars				
1.A	-1.01265	0.002376	-1.10819	-0.91711
2.A	1.202915	0.005754	1.054244	1.351587
3.A	-0.68724	0.006756	-0.84834	-0.52614
4.A	-0.70268	0.003406	-0.81705	-0.5883
5.A	1.901325	0.003063	1.792849	2.0098

6.A	-0.89428	0.001256	-0.96373	-0.82482
7.A	-0.70834	0.003492	-0.82417	-0.59251
8.A	0.175571	0.001588	0.097471	0.253671
9.A	-0.63081	0.002835	-0.73517	-0.52645
10.A	1.55349	0.012403	1.335212	1.771767
11.A	-0.49557	0.058631	-0.97015	-0.02099
12.A	0.747166	0.000648	0.697267	0.797066
13.A	-0.71288	0.004758	-0.84808	-0.57769

Instructional Expenditures, Dollars

1.A	-0.31415	0.00365	-0.43256	-0.19573
2.A	0.777871	0.007734	0.605509	0.950233
3.A	0.571319	0.01146	0.3615	0.781138
4.A	-0.30987	0.004797	-0.44561	-0.17413
5.A	1.745725	0.007162	1.579861	1.911588
6.A	-0.35062	0.001301	-0.42131	-0.27992
7.A	-0.52904	0.00508	-0.66874	-0.38934
8.A	-0.40649	0.002152	-0.49741	-0.31557
9.A	-0.19132	0.004677	-0.32537	-0.05728
10.A	5.464602	0.020636	5.183047	5.746158
11.A	-0.91506	0.097351	-1.52659	-0.30353
12.A	-0.0441	0.000894	-0.1027	0.014512
13.A	0.196154	0.005344	0.052874	0.339434

Number of Undergraduate Degrees Offered, Count

1.A	1.256153	0.004042	1.131549	1.380757
2.A	-1.3589	0.006334	-1.51489	-1.20292
3.A	2.319709	0.009098	2.132759	2.506659
4.A	-0.41986	0.004088	-0.54517	-0.29454
5.A	0.257675	0.004112	0.131993	0.383357
6.A	-0.09262	0.00145	-0.16725	-0.01799
7.A	-1.05221	0.004752	-1.18733	-0.9171
8.A	-0.47477	0.001899	-0.56017	-0.38936
9.A	-1.49077	0.003506	-1.60682	-1.37473
10.A	1.409114	0.016566	1.156852	1.661375
11.A	0.466428	0.078687	-0.08337	1.016222
12.A	0.065317	0.000712	0.013003	0.117631
13.A	1.722988	0.004	1.599032	1.846945

Bachelor's Degree Production, HH Index

1.A	-0.53171	0.00124	-0.60074	-0.46269
2.A	2.626134	0.004533	2.494177	2.758092
3.A	-0.5439	0.003623	-0.66188	-0.42592
4.A	-0.3848	0.00168	-0.46513	-0.30447
5.A	-0.32995	0.001869	-0.41469	-0.24522
6.A	-0.32553	0.000476	-0.36831	-0.28275
7.A	0.619003	0.003645	0.500672	0.737335
8.A	-0.08772	0.000888	-0.14612	-0.02932
9.A	3.018553	0.001964	2.931699	3.105407
10.A	-0.44387	0.006692	-0.6042	-0.28353
11.A	-0.04962	0.03179	-0.39908	0.29983
12.A	-0.33241	0.000288	-0.36567	-0.29915
13.A	-0.53569	0.001564	-0.61321	-0.45817

Tenure and Tenure-track Faculty, Percent

1.A	0.458016	0.002458	0.360838	0.555193
2.A	-0.93046	0.005745	-1.07901	-0.78191
3.A	0.213387	0.005619	0.066474	0.3603
4.A	0.318388	0.003024	0.210617	0.426158
5.A	0.507575	0.00253	0.408999	0.60615
6.A	0.570533	0.000725	0.517778	0.623288
7.A	-1.5954	0.002665	-1.69658	-1.49423
8.A	-1.60471	0.001216	-1.67305	-1.53637
9.A	-1.53082	0.002437	-1.62758	-1.43406
10.A	0.025846	0.01034	-0.17345	0.225143
11.A	-1.69586	0.049117	-2.13023	-1.26148
12.A	0.614436	0.000444	0.573131	0.655742
13.A	0.310292	0.002576	0.210814	0.409769

Science and Engineering Research Expenditures, Dollars

1.A	-0.13505	0.002019	-0.22312	-0.04698
2.A	-0.22834	0.003856	-0.35005	-0.10663
3.A	3.465326	0.009556	3.273731	3.656922
4.A	-0.21725	0.002544	-0.31612	-0.11839
5.A	0.067427	0.003277	-0.04478	0.179632
6.A	-0.23065	0.000689	-0.28211	-0.1792
7.A	-0.23679	0.002649	-0.33766	-0.13591
8.A	-0.23588	0.001134	-0.30188	-0.16988
9.A	-0.23678	0.002342	-0.33164	-0.14192
10.A	6.190893	0.01116	5.983845	6.397942

11.A	-0.23679	0.052992	-0.68797	0.214395
12.A	-0.22994	0.000448	-0.27143	-0.18845
13.A	0.807378	0.003066	0.698854	0.915903
Non-Science and Engineering Research Expenditures, Dollars				
1.A	-0.10576	0.003541	-0.22239	0.010863
2.A	-0.24152	0.005809	-0.39091	-0.09213
3.A	3.922193	0.009682	3.72934	4.115045
4.A	-0.22436	0.003837	-0.34577	-0.10294
5.A	0.11103	0.004008	-0.01305	0.235111
6.A	-0.2387	0.001039	-0.30187	-0.17554
7.A	-0.24553	0.003993	-0.36938	-0.12167
8.A	-0.24316	0.001709	-0.32418	-0.16213
9.A	-0.24552	0.003531	-0.36199	-0.12906
10.A	4.572332	0.016823	4.318118	4.826547
11.A	-0.24553	0.079887	-0.7995	0.308446
12.A	-0.23778	0.000668	-0.28841	-0.18714
13.A	1.025839	0.006448	0.868451	1.183227
PhD Offerings, Count				
1.A	0.228015	0.003344	0.114676	0.341353
2.A	-0.38257	0.003621	-0.50051	-0.26463
3.A	3.499883	0.005222	3.358254	3.641512
4.A	-0.18541	0.002278	-0.27896	-0.09185
5.A	0.33836	0.003741	0.218479	0.458241
6.A	-0.35871	0.000637	-0.40818	-0.30925
7.A	-0.37685	0.002292	-0.47069	-0.28301
8.A	-0.37795	0.000993	-0.43972	-0.31619
9.A	-0.41629	0.002	-0.50394	-0.32864
10.A	3.354089	0.009503	3.163026	3.545152
11.A	-0.05102	0.045136	-0.46741	0.365384
12.A	-0.3351	0.00041	-0.37477	-0.29543
13.A	2.467646	0.003041	2.359556	2.575736
/				
var(e.zadm~A	0.682855	0.000607	0.634554	0.731156
var(e.zadm~A	0.682855	0.000607	0.634554	0.731156
var(e.zadm~A	0.682855	0.000607	0.634554	0.731156
var(e.zadm~A	0.682855	0.000607	0.634554	0.731156
var(e.zadm~A	0.682855	0.000607	0.634554	0.731156

var(e.zadm~A	0.682855	0.000607	0.634554	0.731156
var(e.zadm~A	0.682855	0.000607	0.634554	0.731156
var(e.zadm~A	0.682855	0.000607	0.634554	0.731156
var(e.zadm~A	0.682855	0.000607	0.634554	0.731156
var(e.zadm~A	0.682855	0.000607	0.634554	0.731156
var(e.zadm~A	0.682855	0.000607	0.634554	0.731156
var(e.zadm~A	0.682855	0.000607	0.634554	0.731156
var(e.zadm~A	0.682855	0.000607	0.634554	0.731156
var(e.zdis~A	0.718365	0.000711	0.66612	0.77061
var(e.zdis~A	0.718365	0.000711	0.66612	0.77061
var(e.zdis~A	0.718365	0.000711	0.66612	0.77061
var(e.zdis~A	0.718365	0.000711	0.66612	0.77061
var(e.zdis~A	0.718365	0.000711	0.66612	0.77061
var(e.zdis~A	0.718365	0.000711	0.66612	0.77061
var(e.zdis~A	0.718365	0.000711	0.66612	0.77061
var(e.zdis~A	0.718365	0.000711	0.66612	0.77061
var(e.zdis~A	0.718365	0.000711	0.66612	0.77061
var(e.zdis~A	0.718365	0.000711	0.66612	0.77061
var(e.zdis~A	0.718365	0.000711	0.66612	0.77061
var(e.zdis~A	0.718365	0.000711	0.66612	0.77061
var(e.zdis~A	0.718365	0.000711	0.66612	0.77061
var(e.zeft~A	0.238222	0.000092	0.219426	0.257017
var(e.zeft~A	0.238222	0.000092	0.219426	0.257017
var(e.zeft~A	0.238222	0.000092	0.219426	0.257017
var(e.zeft~A	0.238222	0.000092	0.219426	0.257017
var(e.zeft~A	0.238222	0.000092	0.219426	0.257017
var(e.zeft~A	0.238222	0.000092	0.219426	0.257017
var(e.zeft~A	0.238222	0.000092	0.219426	0.257017
var(e.zeft~A	0.238222	0.000092	0.219426	0.257017
var(e.zeft~A	0.238222	0.000092	0.219426	0.257017
var(e.zeft~A	0.238222	0.000092	0.219426	0.257017
var(e.zeft~A	0.238222	0.000092	0.219426	0.257017
var(e.zeft~A	0.238222	0.000092	0.219426	0.257017
var(e.zeft~A	0.238222	0.000092	0.219426	0.257017
var(e.zeft~A	0.279724	0.00015	0.255739	0.303708
var(e.zeft~A	0.279724	0.00015	0.255739	0.303708
var(e.zeft~A	0.279724	0.00015	0.255739	0.303708
var(e.zeft~A	0.279724	0.00015	0.255739	0.303708
var(e.zeft~A	0.279724	0.00015	0.255739	0.303708
var(e.zeft~A	0.279724	0.00015	0.255739	0.303708

var(e.zeft~A	0.279724	0.00015	0.255739	0.303708
var(e.zeft~A	0.279724	0.00015	0.255739	0.303708
var(e.zeft~A	0.279724	0.00015	0.255739	0.303708
var(e.zeft~A	0.279724	0.00015	0.255739	0.303708
var(e.zeft~A	0.279724	0.00015	0.255739	0.303708
var(e.zeft~A	0.279724	0.00015	0.255739	0.303708
var(e.zeft~A	0.279724	0.00015	0.255739	0.303708
var(e.zftf~A	0.689041	0.000686	0.637716	0.740366
var(e.zftf~A	0.689041	0.000686	0.637716	0.740366
var(e.zftf~A	0.689041	0.000686	0.637716	0.740366
var(e.zftf~A	0.689041	0.000686	0.637716	0.740366
var(e.zftf~A	0.689041	0.000686	0.637716	0.740366
var(e.zftf~A	0.689041	0.000686	0.637716	0.740366
var(e.zftf~A	0.689041	0.000686	0.637716	0.740366
var(e.zftf~A	0.689041	0.000686	0.637716	0.740366
var(e.zftf~A	0.689041	0.000686	0.637716	0.740366
var(e.zftf~A	0.689041	0.000686	0.637716	0.740366
var(e.zftf~A	0.689041	0.000686	0.637716	0.740366
var(e.zftf~A	0.689041	0.000686	0.637716	0.740366
var(e.zftf~A	0.689041	0.000686	0.637716	0.740366
var(e.zurm~A	0.516441	0.000425	0.47602	0.556862
var(e.zurm~A	0.516441	0.000425	0.47602	0.556862
var(e.zurm~A	0.516441	0.000425	0.47602	0.556862
var(e.zurm~A	0.516441	0.000425	0.47602	0.556862
var(e.zurm~A	0.516441	0.000425	0.47602	0.556862
var(e.zurm~A	0.516441	0.000425	0.47602	0.556862
var(e.zurm~A	0.516441	0.000425	0.47602	0.556862
var(e.zurm~A	0.516441	0.000425	0.47602	0.556862
var(e.zurm~A	0.516441	0.000425	0.47602	0.556862
var(e.zurm~A	0.516441	0.000425	0.47602	0.556862
var(e.zurm~A	0.516441	0.000425	0.47602	0.556862
var(e.zurm~A	0.516441	0.000425	0.47602	0.556862
var(e.zurm~A	0.516441	0.000425	0.47602	0.556862
var(e.zPel~A	0.571855	0.000444	0.53056	0.613149
var(e.zPel~A	0.571855	0.000444	0.53056	0.613149
var(e.zPel~A	0.571855	0.000444	0.53056	0.613149
var(e.zPel~A	0.571855	0.000444	0.53056	0.613149
var(e.zPel~A	0.571855	0.000444	0.53056	0.613149
var(e.zPel~A	0.571855	0.000444	0.53056	0.613149
var(e.zPel~A	0.571855	0.000444	0.53056	0.613149

var(e.zPel~A	0.571855	0.000444	0.53056	0.613149
var(e.zPel~A	0.571855	0.000444	0.53056	0.613149
var(e.zPel~A	0.571855	0.000444	0.53056	0.613149
var(e.zPel~A	0.571855	0.000444	0.53056	0.613149
var(e.zPel~A	0.571855	0.000444	0.53056	0.613149
var(e.zPel~A	0.571855	0.000444	0.53056	0.613149
var(e.zHHI~A	0.632679	0.000537	0.587243	0.678115
var(e.zHHI~A	0.632679	0.000537	0.587243	0.678115
var(e.zHHI~A	0.632679	0.000537	0.587243	0.678115
var(e.zHHI~A	0.632679	0.000537	0.587243	0.678115
var(e.zHHI~A	0.632679	0.000537	0.587243	0.678115
var(e.zHHI~A	0.632679	0.000537	0.587243	0.678115
var(e.zHHI~A	0.632679	0.000537	0.587243	0.678115
var(e.zHHI~A	0.632679	0.000537	0.587243	0.678115
var(e.zHHI~A	0.632679	0.000537	0.587243	0.678115
var(e.zHHI~A	0.632679	0.000537	0.587243	0.678115
var(e.zHHI~A	0.632679	0.000537	0.587243	0.678115
var(e.zHHI~A	0.632679	0.000537	0.587243	0.678115
var(e.zHHI~A	0.632679	0.000537	0.587243	0.678115
var(e.zNet~A	0.603184	0.000525	0.558272	0.648095
var(e.zNet~A	0.603184	0.000525	0.558272	0.648095
var(e.zNet~A	0.603184	0.000525	0.558272	0.648095
var(e.zNet~A	0.603184	0.000525	0.558272	0.648095
var(e.zNet~A	0.603184	0.000525	0.558272	0.648095
var(e.zNet~A	0.603184	0.000525	0.558272	0.648095
var(e.zNet~A	0.603184	0.000525	0.558272	0.648095
var(e.zNet~A	0.603184	0.000525	0.558272	0.648095
var(e.zNet~A	0.603184	0.000525	0.558272	0.648095
var(e.zNet~A	0.603184	0.000525	0.558272	0.648095
var(e.zNet~A	0.603184	0.000525	0.558272	0.648095
var(e.zNet~A	0.603184	0.000525	0.558272	0.648095
var(e.zNet~A	0.603184	0.000525	0.558272	0.648095
var(e.zTui~A	0.234523	0.000177	0.208433	0.260613
var(e.zTui~A	0.234523	0.000177	0.208433	0.260613
var(e.zTui~A	0.234523	0.000177	0.208433	0.260613
var(e.zTui~A	0.234523	0.000177	0.208433	0.260613
var(e.zTui~A	0.234523	0.000177	0.208433	0.260613
var(e.zTui~A	0.234523	0.000177	0.208433	0.260613
var(e.zTui~A	0.234523	0.000177	0.208433	0.260613
var(e.zTui~A	0.234523	0.000177	0.208433	0.260613

var(e.zTui~A	0.234523	0.000177	0.208433	0.260613
var(e.zTui~A	0.234523	0.000177	0.208433	0.260613
var(e.zTui~A	0.234523	0.000177	0.208433	0.260613
var(e.zTui~A	0.234523	0.000177	0.208433	0.260613
var(e.zTui~A	0.234523	0.000177	0.208433	0.260613
var(e.zins~t	0.389402	0.000199	0.361744	0.417061
var(e.zins~t	0.389402	0.000199	0.361744	0.417061
var(e.zins~t	0.389402	0.000199	0.361744	0.417061
var(e.zins~t	0.389402	0.000199	0.361744	0.417061
var(e.zins~t	0.389402	0.000199	0.361744	0.417061
var(e.zins~t	0.389402	0.000199	0.361744	0.417061
var(e.zins~t	0.389402	0.000199	0.361744	0.417061
var(e.zins~t	0.389402	0.000199	0.361744	0.417061
var(e.zins~t	0.389402	0.000199	0.361744	0.417061
var(e.zins~t	0.389402	0.000199	0.361744	0.417061
var(e.zins~t	0.389402	0.000199	0.361744	0.417061
var(e.zins~t	0.389402	0.000199	0.361744	0.417061
var(e.zins~t	0.389402	0.000199	0.361744	0.417061
var(e.zUG_~A	0.314748	0.000139	0.29161	0.337886
var(e.zUG_~A	0.314748	0.000139	0.29161	0.337886
var(e.zUG_~A	0.314748	0.000139	0.29161	0.337886
var(e.zUG_~A	0.314748	0.000139	0.29161	0.337886
var(e.zUG_~A	0.314748	0.000139	0.29161	0.337886
var(e.zUG_~A	0.314748	0.000139	0.29161	0.337886
var(e.zUG_~A	0.314748	0.000139	0.29161	0.337886
var(e.zUG_~A	0.314748	0.000139	0.29161	0.337886
var(e.zUG_~A	0.314748	0.000139	0.29161	0.337886
var(e.zUG_~A	0.314748	0.000139	0.29161	0.337886
var(e.zUG_~A	0.314748	0.000139	0.29161	0.337886
var(e.zUG_~A	0.314748	0.000139	0.29161	0.337886
var(e.zUG_~A	0.314748	0.000139	0.29161	0.337886
var(e.zHHI~A	0.127159	2.55E-05	0.117259	0.137059
var(e.zHHI~A	0.127159	2.55E-05	0.117259	0.137059
var(e.zHHI~A	0.127159	2.55E-05	0.117259	0.137059
var(e.zHHI~A	0.127159	2.55E-05	0.117259	0.137059
var(e.zHHI~A	0.127159	2.55E-05	0.117259	0.137059
var(e.zHHI~A	0.127159	2.55E-05	0.117259	0.137059
var(e.zHHI~A	0.127159	2.55E-05	0.117259	0.137059
var(e.zHHI~A	0.127159	2.55E-05	0.117259	0.137059
var(e.zHHI~A	0.127159	2.55E-05	0.117259	0.137059

var(e.zHHI~A	0.127159	2.55E-05	0.117259	0.137059
var(e.zHHI~A	0.127159	2.55E-05	0.117259	0.137059
var(e.zHHI~A	0.127159	2.55E-05	0.117259	0.137059
var(e.zHHI~A	0.127159	2.55E-05	0.117259	0.137059
var(e.zTen~A	0.196468	8.43E-05	0.178477	0.214458
var(e.zTen~A	0.196468	8.43E-05	0.178477	0.214458
var(e.zTen~A	0.196468	8.43E-05	0.178477	0.214458
var(e.zTen~A	0.196468	8.43E-05	0.178477	0.214458
var(e.zTen~A	0.196468	8.43E-05	0.178477	0.214458
var(e.zTen~A	0.196468	8.43E-05	0.178477	0.214458
var(e.zTen~A	0.196468	8.43E-05	0.178477	0.214458
var(e.zTen~A	0.196468	8.43E-05	0.178477	0.214458
var(e.zTen~A	0.196468	8.43E-05	0.178477	0.214458
var(e.zTen~A	0.196468	8.43E-05	0.178477	0.214458
var(e.zTen~A	0.196468	8.43E-05	0.178477	0.214458
var(e.zTen~A	0.196468	8.43E-05	0.178477	0.214458
var(e.zTen~A	0.196468	8.43E-05	0.178477	0.214458
var(e.zCC_~A	0.211969	6.87E-05	0.195727	0.228211
var(e.zCC_~A	0.211969	6.87E-05	0.195727	0.228211
var(e.zCC_~A	0.211969	6.87E-05	0.195727	0.228211
var(e.zCC_~A	0.211969	6.87E-05	0.195727	0.228211
var(e.zCC_~A	0.211969	6.87E-05	0.195727	0.228211
var(e.zCC_~A	0.211969	6.87E-05	0.195727	0.228211
var(e.zCC_~A	0.211969	6.87E-05	0.195727	0.228211
var(e.zCC_~A	0.211969	6.87E-05	0.195727	0.228211
var(e.zCC_~A	0.211969	6.87E-05	0.195727	0.228211
var(e.zCC_~A	0.211969	6.87E-05	0.195727	0.228211
var(e.zCC_~A	0.211969	6.87E-05	0.195727	0.228211
var(e.zCC_~A	0.211969	6.87E-05	0.195727	0.228211
var(e.zCC_~A	0.211969	6.87E-05	0.195727	0.228211
var(e.zCC~1.	0.319549	0.000162	0.294569	0.34453
var(e.zCC~2.	0.319549	0.000162	0.294569	0.34453
var(e.zCC~3.	0.319549	0.000162	0.294569	0.34453
var(e.zCC~4.	0.319549	0.000162	0.294569	0.34453
var(e.zCC~5.	0.319549	0.000162	0.294569	0.34453
var(e.zCC~6.	0.319549	0.000162	0.294569	0.34453
var(e.zCC~7.	0.319549	0.000162	0.294569	0.34453
var(e.zCC~8.	0.319549	0.000162	0.294569	0.34453
var(e.zCC~9.	0.319549	0.000162	0.294569	0.34453
var(e.zCC~10	0.319549	0.000162	0.294569	0.34453

var(e.zCC~11	0.319549	0.000162	0.294569	0.34453
var(e.zCC~12	0.319549	0.000162	0.294569	0.34453
var(e.zCC~13	0.319549	0.000162	0.294569	0.34453
var(e.zPhD~A	0.180544	7.18E-05	0.163935	0.197153
var(e.zPhD~A	0.180544	7.18E-05	0.163935	0.197153
var(e.zPhD~A	0.180544	7.18E-05	0.163935	0.197153
var(e.zPhD~A	0.180544	7.18E-05	0.163935	0.197153
var(e.zPhD~A	0.180544	7.18E-05	0.163935	0.197153
var(e.zPhD~A	0.180544	7.18E-05	0.163935	0.197153
var(e.zPhD~A	0.180544	7.18E-05	0.163935	0.197153
var(e.zPhD~A	0.180544	7.18E-05	0.163935	0.197153
var(e.zPhD~A	0.180544	7.18E-05	0.163935	0.197153
var(e.zPhD~A	0.180544	7.18E-05	0.163935	0.197153
var(e.zPhD~A	0.180544	7.18E-05	0.163935	0.197153
var(e.zPhD~A	0.180544	7.18E-05	0.163935	0.197153
var(e.zPhD~A	0.180544	7.18E-05	0.163935	0.197153