THREE ESSAYS ON STUDENT ACHIEVEMENT, COLLEGE RESOURCES, AND SCHOOL EFFICIENCY

A DISSERTATION SUBMITTED TO THE GRADUATE DIVISION OF THE UNIVERSITY OF HAWAIʻI AT MĀNOA IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

IN

ECONOMICS

DECEMBER 2015

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Keywords: student achievement, cost efficiency, higher education

ACKNOWLEDGEMENTS

Although my life story is one full of roadblocks, I have been blessed to meet people who trusted my abilities and paved the path that I walked on. To my dissertation adviser, Sang-Hyop Lee, I will be forever grateful for the knowledge and wisdom you shared that went along with abundance of patience and understanding. To Raul Fabella, Nimfa Mendoza, James Villafuerte, Brahm Prakash, Lourdes Adriano, and Johanna Boestel, I will always be indebted to all of you for sharing your wealth of experiences and the chance you gave me to grow professionally.

To Erna, Ara, Cathy, Pile, Jen, Bebe, Gemma, Tina, Pong, Baba, Maika, Merv, and Mike who stuck with me through life’s highs and lows, I extremely value our friendships that endured both time and distance. I am as well grateful to all friends who have influenced the person I have become.

Most of all, I would like to thank my family, my parents Bayani and Carmelita, my two siblings Brec and Aki, my dog Casey, Uncle Boy, Nanay, and Tatay, for being my loudest cheerleaders through all these years. You are the foundation on which I built on to finally accomplish the herculean and humbling task of obtaining a Ph.D. degree.

ABSTRACT

This dissertation investigates issues related to three student outcomes, college resources, and school efficiency. The two related research in Chapters 1 and 2 explore the influence of student background characteristics and school resources on the college student outcomes of attendance, completion, and persistence. Using a merged dataset of the National Longitudinal Survey of the Youth 1979 Geocode version and the Integrated Postsecondary Education System, the omitted variable bias common in standard education production function approach is mitigated as well as made available several resource indicators that both enabled a comprehensive analysis of the impact of school resources on student persistence and completion and the application of the multiple indicator solution variant of the instrumental variables methodology to account for both time-constant and time-varying unobserved heterogeneity. Overall, the empirical findings reveal that ability, gender, marital status, and precollege preparation are strong predictors of student success in college, while greater school resources matter only for low-resource institutions with the exception of financial aid spending. More precisely, the estimation results suggest that a 10 percent increase in financial aid spending can raise student completion and persistence across different spending levels by 0.8-2.5 and 0.6-3.4 percentage points, respectively.

Finally in Chapter 3, I evaluate the cost efficiency of American colleges and universities as well as assess their plausible responses when economic shocks, such as those in 2008 and the fragility of the global economy that lingered thereafter, adversely impact their revenue structure using a one-step, panel data variant of the stochastic frontier analysis methodology. The results suggest that the US higher education sector is about 77 percent cost-efficient, implying that schools can maintain their output levels while absorbing budget cuts. Further investigation also imply that failure to account for school quality in cost analyses misattributes the impact of quality on costs onto institutional control, while inefficiency effects are influenced by colleges' student, staff, and cost share characteristics. More precisely, cost inefficiency falls with increases in the instruction cost share and generally rises with the shares of part-time students, undergraduate students aged 25 and over, female instructors, professors, nonwhite staff, and research spending.

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1.1. Introduction

The 1966 Coleman Report on Equality of Educational Opportunity spurred a long and ongoing debate when it suggested that additional school resources fail to contribute to student achievement in United States (US) public primary and secondary levels of education. For these schools, a survey of the literature by Hanushek (2002) identified at least 376 separately published estimates that refuted or supported the report's provocative findings from as early as 1994. Although there is a lot to gain from the policy implications of these types of research, it is surprising that the same kind of attention has not been garnered for higher education.

School resources impact students both directly and indirectly. In the educational production function approach, student achievement is an output created by a combination of the various inputs (Hanushek, 1997; Hanushek, 2002) of individual, family, household, environmental, peer, and school characteristics. In this context, more and higher-quality school resources, such as a higher faculty-student ratio or higher per-student spending, are presumed as investments for a learning environment that promotes greater student achievement. Within the credentialism view, college quality, reflected in school resources, is rewarded in the labor market by signaling the quality of students. Hence, the higher returns to education associated with college quality provides the incentive for student achievement.

The causal link from college resources to student outcomes is important in many respects. Among college students who incur both implicit and explicit college-going costs, the realization of the college wage premium facilitated by school investments in their education most likely provides the greatest incentive to obtaining a college degree. Recent estimates by Carnevale, Rose, and Cheah (2011) indicate that in 1999, the average lifetime earnings of a bachelor's degree holder were 75 percent higher than those of a high school graduate, and this college premium increased to 84 percent by 2009. Meanwhile, causal estimates of the returns to a completed year in college range from 9 to 14 percent (Card, 1995; Bound and Turner, 2002; Oreopoulos and Petronijevic, 2013; Zimmerman, 2014). The returns of a college diploma are likely to be more compelling for students attending four-year, private, not-for-profit and for-profit institutions who on average paid about $25,000 in tuition and fees during the 2013–2014 academic year. In contrast, the huge subsidies that public higher education institutions receive from federal and state governments should hold school administrators accountable to policymakers and taxpayers by providing acceptable student outcome statistics. During the 2006–2007 academic year[1], per-student spending and tuition and fees of four-year public colleges and universities were about $33,000 and $6,000, respectively, and increased by the 2012–2013 academic year to $38,000 and $8,000, respectively.

Due mainly to data limitations, the approach taken by the literature to separately examine the effects of individual, family, and household (collectively termed student background) characteristics, on the one hand, and school resources, on the other, on college student achievement can lead to an omitted variable bias in the school resource estimators that manifests through inflated resource coefficients (Hanushek, Rivkin, and Taylor, 1996). The omitted variable bias is addressed in this research by merging two panel[2] datasets: the individual-level National Longitudinal Survey of the Youth 1979 (NLSY79) and its Geocode Supplement, and the institutional-level Integrated Postsecondary Education Data System (IPEDS). Using the institution-specific Federal Interagency Committee on Education (FICE) or the IPEDS school codes that are reported in both datasets, the NLSY79 survey respondents and their socioeconomic characteristics were matched with their school information found in the IPEDS. Since IPEDS is also a wealthy source of school resource information, both real and financial, the merging of the two datasets also provides an opportunity for an extensive assessment of the impact of institutional resources on student outcomes and facilitates the use of the multiple indicator solution (MIS) approach to solving the endogeneity problem inherent in school resources.

In this research, I focus on two college achievement outcomes: student attendance and completion. More precisely, I investigate the impacts of student background characteristics on college attendance, as well of school resources, on college completion. The results reveal that: (1) separate treatments of the effects of student background and school characteristics on student completion will lead to an omitted variable bias that manifests in this application through overestimated ability coefficients if school resources are not controlled in the education production function specification; (2) ability, gender, marital status, and precollege preparation influence

[1] 2014 Digest of Education Statistics Tables. https://nces.ed.gov/programs/digest/2014menu_tables.asp.

[2] Due to the repetitive nature of the college attendance and completion decisions, cross-sectional analysis will yield consistent but inefficient results (Verbeek, 2012).

college attendance; (3) ability, gender, and school resources positively impact college completion; (4) on average, a one-hundredth of a point rise in faculty-student ratio is estimated to raise the probability of completion by about 36 percentage points; (5) on average, a 10 percent rise in per-student instruction, research, or academic-related spending is estimated to raise completion probability by about 3.5 percentage points; (6) on average, a 10 percent increase in financial aid or total spending is estimated to lead to an increase in completion probability of about 2.5 percentage points; and (7) school resources generally influence student completion in low-resource scenarios.

1.2. Literature Review

The extensive research conducted on the causal relationship from school resources to student achievement, with Hanushek (2002) identifying more than 300 published estimates at the primary and secondary levels, has failed to resolve the issue, although more recent evidence at the higher education level points to nontrivial effects. At the tertiary level, student achievement has been measured in a number of ways, including by the schools to which students send SAT scores, attendance, retention, completion, success in the labor market, and subjective self-evaluation of student gains in several skills. While evidence on school resource effects is still warranted, the higher education literature is in general agreement that individual, family, and environmental characteristics strongly influence college achievement outcomes (Evans and Schwab [1995], Ganderton and Santos [1995], Kane [1995], Light [1995], Eide and Showalter [1998], Light and Strayer [2000], Toutkouhsian and Smart [2001], Chevalier and Lanot [2002], Dynarski [2002, 2003], Sandy, Gonzalez, and Hilmer [2006], Bound and Turner [2007], Jepsen [2008], Bound, Lovenhiem, and Turner [2010]) with a unifying argument that the calculation of individuals of the expected benefits and costs of college achievement can be proxied by, among others: student ability, precollege preparation, gender, race, martial status, parents' education, family size, income, socioeconomic status, and labor market opportunities.

Meanwhile, three alternative theories also explain how colleges can facilitate greater achievement. In the education production function framework, more and better school inputs in the form of greater spending, high-quality teachers, or smaller class sizes can be viewed as investments in achieving better student performance. Meanwhile, the credentialism theory attributes the perceived quality of the degrees and education awarded by an institution reflected in school resources as a signal of the underlying abilities, motivation, and other valuable traits of a school's students that are rewarded in the labor market (Becker, 1993). Finally, in the context of demand for higher education, Bound and Turner (2007) illustrate that a student's willingness to pay a given amount of tuition increases with the quality of education that a school offers, which is directly observed in school resource allocations, e.g., per-student spending.

The failure to conclusively link school resources to college achievement is partly due to the inability of past research to jointly control for student background and institutional characteristics in college achievement specifications, which results in omitted variable bias in the estimators. For the United Kingdom, Chevalier and Lanot (2002) used datasets from two cohorts to estimate the relative effects of parental characteristics and financial situation, and simulate the impact of an education subsidy that is transferred through the father's income on the probability of a student leaving school after the compulsory level of education. Although they were able to simulate the ineffectiveness of financial aid sourced through a student's father, the estimators from which this result was obtained were already subject to omitted variable bias since school resources were left out in the achievement specification. Moreover, Hanushek, Rivkin, and Taylor (1996) demonstrated that this bias problem is exacerbated for resource data that are aggregated to the level of the omitted variable, implying that the use of state-level data would likely lead to unreliable estimators. For instance, Ram (2004), without controlling for student background characteristics, used state-level panel data to estimate the effect of per-student spending on SAT achievement scores and found modest spending effects, particularly on the math component.

In an effort to incorporate institutional resources in the analysis, an alternative group of research controls for general higher education or secondary school characteristics. The research of St. John et al. (2001) investigated the impact of SAT and ACT scores, the merit-aware index[3], attending a research university, and living on campus on college persistence and revealed that students who pursue college at a research university and live on campus are more likely to complete their first year in college. Jepsen (2008), using a multinomial probit specification to examine the relative impacts of gender, race, ethnicity, and immigration on college attendance,

[3] The merit-aware index is defined as the difference between a student's SAT/ACT score and the average SAT/ACT score of all college-going students in the student's high school.

and attainment of two-year and four-year degrees, also controlled for high school characteristics, such as the proportion of the student population eligible for free or reduced price lunch, the offering of vocational education, and eighth-grade test scores. Lastly, Ganderton and Santos (1995) found that educational patterns while in college, such as attendance interruptions and initial attendance at a two-year college, influence Hispanic college attendance and completion behavior.

A potential solution to the bias problem is to utilize individual-level, state survey data that are more likely to report information on a respondent's college achievement, student background characteristics, and institutional characteristics. St. John et al. (2001) and Toutkoushian (2001) used data for Indiana and New Hampshire, respectively, while Deming et al. (2014) investigated a more geographically concentrated group of high school students in the Charlotte-Mecklenburg school district in North Carolina. Unfortunately, the essential variables in the production function specification of college achievement are rarely reported in a single nationally representative survey data.[4] Light (1995) used a sample of young men from NLSY79 and a semiparametric proportional hazard method for grouped duration data to explore the probability of reenrollment in a higher education demand framework. Her research found that relative costs and benefits determine reenrollment decisions, particularly favorable labor market opportunities, and high tuition levels lower the hazard of reenrollment. In Light and Strayer (2000), merged data of the NLSY79 Geocode version and IPEDS enabled the joint estimation of the relative impacts of background and institutional characteristics on college completion. Using the 1982 Barron's College Admissions Selector, median SAT score, and per-student spending as indicators of college quality, they demonstrated with a two-period, simultaneous model[5] that the likelihood of graduation rises when the levels of student ability and college quality positively match.

An ideal setup of standard achievement specification is demonstrated by Eide and Showalter (1998) using a quintile regression approach and the High School and Beyond longitudinal data of sophomore public high school students. Controlling for individual, family, and

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[4] For instance, the NLSY79 reports student outcomes and background characteristics of respondents, but not the characteristics of the higher education institutions they attended. The nationally representative datasets used in the college achievement literature include: Current Population Survey (CPS), National Longitudinal Study of the High School Class of 1972 (NLS72), NLSY79, High School and Beyond (HSB) Survey, National Educational Longitudinal Study of 1988 (NELS88), and Beginning Postsecondary Study (BPS).
[5] In their two-period model, the first period decision is a multinomial probit model of attendance choice among college quality categories and the second period decision is a binomial probit model of college completion.

environmental characteristics, they examined the impact of school resources, e.g., pupil-teacher ratio, school year length, proportion of teachers with advanced degrees, school enrollment, per-student spending, at different points of the conditional distribution of math achievement test score gains and found that while school resources, on average, might not influence achievement, their impact can vary across the achievement distribution. Meanwhile, another study by Toutkouhsian and Smart (2001) evaluated student outcomes in terms of self-assessed student gains on work/interpersonal skills, learning/knowledge, tolerance/awareness, preparation for graduate school, and communication skills. Using survey data from the Cooperative Institutional Research Program (CIRP), they found statistically significant impacts of family background, student characteristics acquired in college, and institutional per-student spending on these alternative achievement measures.

Despite the availability of comprehensive data that report all desired explanatory variables in a student achievement specification, school resource indicators are also potentially subject to endogeneity. For instance, high school choice might be tied to a student's religion (Evans and Schwab, 1995), school spending could be influenced by expected standardized achievement test performance of a cohort of students (Papke and Wooldridge, 2008), or the school resource indicator might simply be measured with error. More formally, Bound and Turner's (2007) higher education demand theory indicates that a student's willingness to pay a given price to attend an institution increases with the quality of education offered by the school, represented by school resources. Meanwhile, the credentialism view (Becker, 1993) explains that the degrees and education awarded by an institution signal the underlying abilities, persistence, and other valuable traits of its students who self-select into these institutions possibly with external influences.

The standard approach to purge the endogeneity inherent in school resource measures has been the application of the instrumental variables (IV) method, which finds or creates exogenous variation in the school resource variable.[6] In a study that relates to Michigan fourth graders, Papke and Wooldridge (2008) utilized a 1994–1995 shift in funding policy, known as the "foundation grant", that narrows the spending gap between the lowest and highest spending districts to instrument for average per-student spending. For higher education, Evans and Schwab (1995) used

[6] For a more detailed discussion on the instrumental variables approach, see Angrist and Krueger (2001).

a student's religion and the Catholic composition of the county location of a student's high school as instruments to identify the effect of Catholic high school attendance on the probability of finishing high school and starting college.

The IV method has also been used to address the endogeneity of schooling in several studies that relate to the returns to schooling literature. Among instruments that were used to identify the effect of schooling on wages include the twin-reported level of education in Ashenfelter and Krueger (1994), college proximity in Card (1995), and family background variables and sibling's schooling level in Blackburn and Neumark (1995). Also, Card (1995) used the Knowledge of the World of Work (KWW) test score as an instrument for the IQ test score to identify the effects of ability on labor market outcomes.

More recent research exploits discrete policy shifts or exogenous demographic variation, more popularly known in the literature as natural experiments, to identify the causal effect of school resources. Using achievement test scores as the outcome variable, Krueger (1999) instrumented for class size with random assignment of students to a small- or normal-size class. Two studies by Dynarski (2002, 2003) examine the effects of a discrete policy shift, the introduction of Help Outstanding Pupils Educationally (HOPE) Scholarship Program that provided financial support to Georgia high school graduates with at least a B average to attend state colleges and the elimination of the Social Security Student Benefit Program in 1982 that would have made monthly payments to the college-going, under-22 children of deceased, disabled, or retired beneficiaries, on college choice behavior. She found that a $1,000 increase in college subsidy can raise attendance rates among high school graduates by 4–6 percentage points and completed level of schooling by 0.16 years. Multiple studies of veterans' educational benefits in the post-World War II period also found that GI Bills raised the schooling of veterans (Angrist, 1993; Stanley, 2003 Turner and Bound, 2003 Bound and Turner, 2002). On the other hand, results from the introduction of Pell Grants indicate mixed results. Hansen (1983) and Kane (1995) found that Pell Grants do not influence the college enrollment rate of low-income youth, while Seftor and Turner (2002) estimated a relatively small positive effect on the schooling of a slightly older population, i.e., 0.7 of a percentage point per $1,000 in aid.

In Bound and Turner (2007), plausibly exogenous within-state cohort variation was used to estimate the elasticities of college enrollment and completion to changes in the within-state college-age population. Using both institutional and census data, they found that a 10 percent increase in the college-age population will cause a 4 percent decline in a cohort's college completion rate. Particularly, they point out that this result is mainly driven by shrinking per-student resources when tuition and nontuition revenues of higher education institutions inelastically respond to a changing cohort size instead of adverse shifts in socioeconomic characteristics and precollege preparation.

Bound, Lovenheim, and Turner (2010) explored this issue further by decomposing the decrease in completion rates between the 1972 and 1992 high school classes into demand- and supply-side factors. They simulated the counterfactual completion rates for the 1992 high school class by shifting in a rank-order neutral manner the 1972 high school class distributions of high school percentile test scores, college pupil-teacher ratio, and initial college type attended. Their results indicate that the national trend of declining completion rates among men can be explained by the decline in institutional resources at lower-ranked public universities and the increased proportion of college entry through community colleges.[7] While the observed decline in student precollege preparation also contributed to falling completion rates, student background characteristics, e.g., parental education and income, shifted in ways that offset its effect. In related research, Sandy, Gonzalez, and Hilmer (2006) used the Oaxaca (1973) methodology to decompose the four-year degree completion rate differential between students starting at two-year and four-year postsecondary institutions into variations in student and institutional quality. By comparing results across three national surveys that cover first-year college students from the early 1970s to the early 1990s, they found that changes in institutional quality can explain the majority of variation in completion rates, although the proportion of completion rate decline attributable to student quality has increased over time. As opposed to Bound, Lovenheim, and Turner (2010), however, their research failed to disentangle the roles of institutional resources and levels on the declining trend of completion rates. Finally, Deming et al. (2014) used the random assignment of students by lottery to their first-school choice in the Charlotte-Mecklenburg school district in North

[7] The dominant factors affecting the decline in completion rates are: decline in institutional resources (proxied by college student-faculty ratio) among lower-ranked four-year public institutions and inadequate college student preparation (proxied by math percentile score) among community colleges. Demand- and supply-side factors explain 80 percent of the decline in college completion rates among men, but none of the increase in college completion rates among women.

Carolina to determine the heterogeneous effects of winning the lottery on college enrollment and degree completion. They showed that students who win admission to their first-school choice experience increased peer and school quality characteristics. However, positive responses in terms of better performance in high school and increased probabilities of college enrollment and completion are concentrated among girls.

1.3. Data

1.3.1. A Merged Dataset

Using a standard education production framework, two datasets were merged to investigate the determinants of two college achievement decisions: attendance and completion. In particular, the merged panel dataset enables the joint estimation of the relative impacts of student background and school characteristics on student completion. The first dataset is the National Longitudinal Survey of Youth 1979 (NLSY79) Cohort, which is a longitudinal survey of a sample of American youth born between 1957 and 1964, aged 14–22 when first interviewed in 1979. The survey originally included 12,686 respondents and data are currently available from Round 1 (1979 survey) to Round 25 (2012 survey).[8] The NLSY79 reports information on the individual, family, and household characteristics of survey respondents, including IQ test scores, high school grades, household income, and parents' education, among others.

The second data source is the Integrated Postsecondary Education Data System (IPEDS)[9], which is a database of interrelated surveys conducted by the US Department of Education's National Center for Education Statistics (NCES). The NCES gathers information from every college, university, and technical and vocational institution that participates in the federal student financial aid programs, including data on institutional characteristics, enrollment, finance, completion, and faculty salaries, and is made available to the public through the IPEDS.

In 1984, the Geocode version of NLSY79 started reporting information on the college attendance history of its respondents[10] using the Federal Interagency Committee on Education (FICE) and IPEDS school codes. Using these school codes reported in both datasets, the NLSY79

[8] For more information on NLSY79, see http://www.nlsinfo.org/content/cohorts/nlsy79.
[9] For more information on IPEDS, see http://nces.ed.gov/ipeds/Home/AboutIPEDS.
[10] In each survey year, information is reported for the most recent, and second and third most recent college attended.

survey respondents who attended two-year and four-year public, private not-for-profit, and private for-profit institutions were matched with their school information during attendance, using an enrollment indicator in NLSY79, found in IPEDS. Due to data limitations, international institutions, respondents taking courses from remote locations, and schools whose identification codes could not be verified were dropped from the analysis.

1.3.2. Setting Time Windows

Using data limitations and traditional college-going age years as criteria, the time windows chosen for the analysis are restricted to four-year intervals. Since school attendance reporting in the Geocode version of NLSY79 commenced only in 1984, examination of the influence of school resources on completion from earlier time periods, when the ages of older individuals in the sample were closer to the appropriate college-going age years, is not possible. Meanwhile, the use of more recent time periods is inappropriate since most NLSY79 respondents would have been significantly older in the later years relative to the normal college-going age years of attendance by age 18 and completion by age 22. The corresponding time windows are as follows:

a) For college attendance, the time windows chosen are 1982–1985, 1983–1986, and 1984–1987, when the NLSY79 respondents were aged 17–25, 18–26, and 19–27 in the first year of the respective time windows.
b) For college completion, the time windows chosen are 1984–1987, 1985–1988, and 1986–1989, when the NLSY79 respondents were aged 19–27, 20–28, and 21–29 in the first year of the respective time windows.

Setting the time windows in four-year intervals, although arbitrary, seems reasonable, while at the same time allows for flexibility in the achievement decision-making of students. For instance, it is highly likely that single attendance or completion decisions after a four-year period, during which the student also ages by four years, are final. This is especially the case for the NLSY79 respondents since many of them were already beyond the college-going age years in the identified time windows, i.e., a respondent aged 18 that graduated high school in 1982 but decided not to be a first-time college attendee from 1982 through 1985 would most likely not begin college after 1985 when he would be aged 21.

1.3.3. Imputation of Missing NLSY79 College Data

Prior to merging the NSLY79 and IPEDS data, two imputation methods were carried out to provide a more extensive school attendance history of survey respondents from 1984 through 2004. These procedures involved the use of annual information on enrollment status and the most recent, and second and third most recent schools attended by NLSY79 respondents.

a) Suppose a respondent who was reported to have irregular attendance in the same school for two nonconsecutive years and for whom school attendance information was also missing in the interval period, despite status information indicating college enrollment during the intervening years. In such cases, the school attended during the nonconsecutive years, termed school connectors, was assumed to be the same school attended during the intervening years.[11] To illustrate this, assume that a respondent's most recent college attended was coded for both 1985 and 1988, while college attendance information was missing for the interval years of 1986 and 1987, even though the respondent was reported to have enrolled in college. If the respondent went to the same school in 1985 and 1988, the missing school attendance information in the intervening years of 1986 and 1987 was imputed as the school attended in 1985 and 1988. In searching for these school connectors, a maximum gap of 10 years of discontinuous school attendance was considered. Although this choice is arbitrary and may seem too flexible, it can be safely presumed that a student would have been unlikely to return to the same school if he had not been in attendance for 10 years.[12] Moreover, this procedure does not cause complications for locating FICE connecters for closer, and more reasonable, year gaps.
b) In cases when school connectors could not be established, the missing information for the intervening years for which the individual was reported to have enrolled was imputed with the least recent college attended as reported for the following year for which school attendance data was available. As an illustration, suppose schools attended by a respondent were coded for the most recent college attended in 1984 and

[11] Two procedures were used to establish FICE connectors. The search for a connector would 1) begin with the lead year searching through the previous years and 2) begin with the lag year searching through the succeeding years.
[12] In fact, this proved to be true as FICE connectors were not established for gaps longer than seven years and most FICE connectors were found for a one-year attendance gap.

the most recent and second most recent attended in 1987, with school attendance history information missing for 1985 and 1986 despite information indicating college enrollment. If the most recent college attended in 1984 did not match the second most recent institution attended in 1987 for establishing FICE connectors, missing school attendance information for 1985 and 1986 were instead imputed with the second most recent college attended in 1987, the least recent college attended in the immediate year for which data is available.

1.3.4. <u>College Achievement Dependent Variables</u>

The two binary college achievement dependent variables were defined using annual information on the highest grade completed by NLSY79 respondents. This can be more precisely explained as follows[13]:

a) College attendance is a binary dependent variable assigned a value of 1 for the year if the individual completed grade 13 during the current year, with the condition of completion of grade 12 in the previous year; and 0 otherwise. Clearly, only respondents who completed grades 12 and 13 are part of the analysis as respondents who complete grade 13 would drop out of the sample in the succeeding year. In order to account for the achievement decisions of the NLSY79 respondents who finished grade 13 prior to the observed time windows, these respondents were assigned a college attendance dummy value of 1 on the first year of the time windows. The implications of the adjustment of the college attendance dependent variable on the baseline estimators will be discussed in the results section.
b) College completion is a binary dependent variable assigned a value of 1 for the year if the individual completed grade 16 during the current year, with the condition of completion of grade 15 in the previous year; and 0 otherwise. Hence, only respondents who reached grades 15 and 16 are part of the analysis as those who completed grade 16 would drop out of the sample in the subsequent year. In order to also account for the

[13] Unfortunately, I cannot control for or identify students who were able to attend and complete college before grades 13 and 16, respectively. However, it could be expected that these students reported their highest grade completed appropriately.

achievement decisions of those who completed college prior to the defined time windows, an adjustment similar to the attendance dependent variable was made, i.e., the binary college completion dummy variable for these respondents was assigned a value of 1 on the first year of the time windows. A discussion of the sensitivity of the baseline results to this definition adjustment will also be discussed in the results section.

1.3.5 <u>Descriptive Statistics</u>

Tables 1 and 2 present the summary statistics (means and standard deviations) of the explanatory variables used in the college attendance and completion probability estimations. These tables also report the summary statistics separately for the high achievers (attendance and completion = 1) and low achievers (attendance and completion = 0).

As is evident in Table 1, there is a consistent pattern of student characteristics that can distinguish between college entrants and non-entrants across the three time windows (1982–1985, 1983–1986, and 1984–1987). Using the 1982–1985 data to illustrate, individuals who had gone to college, on average, possessed more favorable individual and socioeconomic characteristics. Namely, on average, they had higher levels of ability (0.38 versus –0.04 Armed Services Vocational Aptitude Battery [ASVAB] standardized test score), were higher achievers in high school (2.09 versus 1.64 high school grade point average [GPA]), had a greater likelihood of never marrying (0.81 for college goers and 0.53 for non-college goers), and had parents with higher educational attainment (11.52 highest grade completed versus 10.07 for father's education; 11.11 highest grade completed versus 9.03 for mother's education).

Using the data from the 1984–1987 time window, the same heterogeneity in student characteristics can also be observed between higher-achieving graduates and lower-achieving non-graduates. In addition, completers were more likely to be white (0.80 versus 0.61) and to have attended schools with greater resources, i.e., higher faculty-spending ratios and spending across all categories.

<Tables 1 and 2 about here>

1.4. Empirical Methodology

1.4.1. The Baseline Model

Given the binary nature of the college achievement dependent variables and the panel data structure, a random-effects probit econometric methodology was used to provide the baseline estimates of the relative impacts of student background and school characteristics on college attendance and completion. Although the choice between the probit and logistic functions in estimating binary response models is mainly a matter of preference on the part of the researcher, the normality assumption of the probit function is convenient in introducing time-constant unobserved heterogeneity in the empirical model. On the other hand, besides a number of interesting time-constant explanatory variables that will be dropped in fixed-effects estimations, the random-effects estimation can be justified by a time-constant unobserved heterogeneity that is potentially minimized by the inclusion of an exhaustive set of covariates.

Moreover, the incidental parameters problem in fixed-effects estimation is important in this application due to the small number of time periods and large number of cross-sectional observations in the data (Papke and Wooldridge, 2008). While incorporating cross-sectional dummies in the specifications can flexibly account for any unobserved heterogeneity in panel data structures, the inconsistency of the fixed-effects estimators worsens as the number of cross-section increases with a fixed number of time periods and translates into inconsistent slope parameter estimators. Finally, the properties of the fixed-effects logit and marginal effect estimators are largely unknown in data with small time periods.

The baseline probit binary response model specified is of the form:

$$E(CA_{it} \mid I_{ji}, F_{kit}, H_{mi}, S_{it}, X_{qit}) = G(\alpha + \beta_j I_{ji} + \chi_k F_{kit} + \delta_m H_{mi} + \lambda_n S_{i,t-1} + \gamma_q X_{qit} + v_{it}) \quad (1)$$

such that

$$CA_{it}^{*} = \alpha + \beta_j I_{ji} + \chi_k F_{kit} + \delta_m H_{mi} + \lambda_n S_{i,t-1} + \gamma_q X_{qit} + v_{it}, CA = 1(CA^{*} > 0) \quad (2)$$

where CA_{it} is the observed college achievement decision, i.e., attendance or completion, of individual i at time t representing an underlying latent variable denoted by $CA_{it}*$, which in turn reflects the unobserved difference in the expected utilities of the two alternative college achievement decisions as in the theory of human capital (Becker, 1993). In equation (2), for instance, the individual is assumed to choose the option to 'achieve', i.e., attend or complete, if the expected net utility of such a decision is greater than zero. The probit functional form is represented by the function *G* as the standard normal cumulative distribution function, which ensures that the expected value of equation (1) is strictly between 0 and 1 for all values of the estimated parameters, α, β_j, χ_k, δ_m, λ_n, and γ_q, and the explanatory variables.

The student background and school characteristics that can impact college achievement in equation (1) are grouped into four categories: individual, family, environmental, and institutional resource characteristics. In equations (1) and (2), I_{ji} is a vector of time-constant individual-level characteristics, j, of individual i; F_{kit} is a vector of time-varying family characteristics, k, for individual i; H_{mi} is a vector of time-constant household characteristics, m, at age 14 for individual i; $S_{i,t-1}$ is a college resource indicator of the college attended by individual i at time $t-1$; and X_{qit} is a vector of time-varying control variables, q, for individual i. The error term v_{it} is assumed to be independent from all the explanatory variables and distributed normally.

Since this research takes the education production function approach and the attendance decision is unlikely to be influenced by supply side-related school resources, only the student background covariates are included in the attendance models. Also, I follow the approaches taken by Ram (2004), Papke (2005), and Roy (2011) who assume that the impact of school resources on achievement decisions is unlikely to be immediate and lag school indicators in the probit function estimations by 1 year.[14, 15]

It can be argued that the ultimate goal of going to college is to eventually obtain and enjoy the expected labor market returns associated with a college degree, while at the same time considering the explicit and implicit costs of attendance on a periodic, e.g., quarterly, semester, or yearly, basis. In the theory of human capital (Becker, 1993), a rational student will make the decision to attend an additional year of college as long as his subjective, updated evaluation of the net marginal benefit of staying in school is positive, whereby the implicit diploma rate of return plausibly becomes relatively more important in the recurring decision process as the student

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[14] The estimators were less compelling in specifications that used contemporaneous school resource indicators.

[15] Papke (2005) found that spending lagged one year had as much, if not a larger, impact on pass rates of Michigan students on a fourth-grade math test, Papke and Wooldridge (2008) used a simple average of spending of current and three lagged years, and Roy (2011) used a spending variable lagged one year. Using state-level panel data to investigate the effect of spending on SAT achievement scores, Ram (2004) lagged per-student spending by a year.

approaches graduation. However, given that costs and expected future earnings related to college achievement decisions are not easily measured, I take the same approach as the literature of using proxy variables to represent these generally unobserved factors.

To control for the opportunity costs facing a student at the time of the college achievement decision, the labor market unemployment rate at the individual's area of residence[16] and the average household income[17] were included as covariates. In addition, student background characteristics, such as inherent ability, precollege education, and socioeconomic background, can improve the probability of college success and consequently the realization of the returns to a college degree.[18] In the empirical models, inherent ability and precollege achievement were proxied by the Armed Services Vocational Aptitude Battery (ASVAB) standardized test scores[19] and high school GPA[20], respectively, and socioeconomic status was proxied by the father's and mother's education, and indicators of whether reading-related materials (newspapers, magazines, or library cards) were available and the individual lived with both parents in the household when the respondent was 14 years old.

As mentioned, the merged NLSY79 and IPEDS dataset enables the joint examination of the relative effects of student background characteristics and school resources, as well as the influence of multiple resource indicators on college completion.[21] The following school resource

[16] For more information on the calculation of the local labor market unemployment rate for NLSY79 respondents, see https://www.nlsinfo.org/content/cohorts/nlsy79/other-documentation/codebook-supplement/nlsy79-appendix-7-unemployment-rate.

[17] To represent a household's college affordability or alternative labor market options, the mean household income was computed using the income earned in the three years prior to the college achievement decision.

[18] The implicit diploma rate of return might rise further with a relatively more favorable mix of inherent ability, prior achievement, and college education.

[19] In an effort by the U.S. Departments of Defense and Military Services to update the norms of the ASVAB, it was administered in 1980 to the nationally representative sample of NLSY79 respondents. It consists of a battery of 10 tests that measure knowledge and skill in the following areas: general science, arithmetic reasoning, word knowledge, paragraph comprehension, numerical operations, coding speed, auto and shop information, mathematics knowledge, mechanical comprehension, and electronics information. For more information on ASVAB, see https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/education/aptitude-achievement-intelligence-scores.

[20] The NLSY Transcript Surveys collected during 1980–1983 the high school transcript information of 8,778 civilian NLSY79 respondents, each for up to 64 courses, who were 17 years of age or older and were expected to complete high school within the United States. The author's calculation of high school GPA is the mean of the grades for up to 64 courses collected for each individual. For more information on the NLSY79 Transcript Surveys, see https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/education/school-transcript-surveys.

[21] I hypothesize that school resources do not directly affect attendance decisions by assuming that a student will determine attendance at an institution with the quality (proxied by school resources) he desires based on his ability to pay (represented by the household income variable in the attendance specifications).

indicators, classified in the literature as either real or financial (Hanushek, 1997, 2002), were obtained from IPEDS: the faculty-student ratio; instruction, research, and academic-related[22], scholarships and fellowships; and total per-student spending categories. These multiple resource indicators will also prove useful in providing a solution to the endogeneity problem inherent in school choice. Other control variables incorporated in the specifications are: gender (male dummy), race (white dummy), marital status (never-married dummy), age of individual, institutional control (public dummy), institutional level (two-year institution dummy), regional location of the institution (West, East, South, and Midwest; South as base group), and year dummies. The individual, family, household, and environmental characteristics were obtained from the NLSY79 data and its Geocode Supplement, while school resources and characteristics data were sourced from IPEDS. All nominal dollar values were converted into real terms using the All Urban Consumers CPI (1982–1984 = 100) as the price deflator as reported by the US Bureau of Labor Statistics.

1.4.2. Addressing the Endogeneity Issue

There are a few reasons than can cause the endogeneity of school resources in the structural equation. First, the college achievement decisions of students or the evolving objectives of school administrators can impact the annual budget allocation decisions of school or state officials. It is highly likely, for instance, that low enrollment rates or a greater focus by administrators on student completion will lead to more resources being targeted towards academic-related spending (Papke and Wooldridge, 2008), while state budgets, federal appropriations, and restrictions on tuition charges determine the revenue structure of public higher education institutions (Bound and Turner, 2007; Bound, Lovenheim, and Turner, 2010). On the other hand, school choice can also be influenced by a student's motivation, parents, siblings, high school counselors, peers, and religion, among others (Evans and Schwab, 1995).

Since several resource indicators were available from IPEDS, the multiple indicator solution (MIS) can be used to address school choice endogeneity or resource measurement error.

[22] Academic-related spending is the sum of instruction, research, and academic support spending.

The MIS is an instrumental variables (IV) estimation technique that can be applied when there are two or more indicators of an endogenous or error-ridden explanatory variable (Wooldridge, 2010).

Suppose there are two school resource (*N*) indicators, S_1 and S_2, both of which can proxy for investment on student learning, student credentials, or school quality and are redundant in structural equation (1). By definition:

$$S_1 = \pi_o + \pi_1 N + a_1 \tag{3}$$

$$S_2 = \theta_0 + \theta_1 N + a_2 \tag{4}$$

where $\pi_1>0$ and $\theta_1>0$, and a_1 and a_2 are error terms.[23]

For S_1 and S_2 to be valid instruments for each other, the following standard MIS conditions must be satisfied:

$$\text{cov}(N, a_i) = 0,\ i = 1, 2 \tag{5}$$

$$\text{cov}(X, a_i) = 0,\ i=1,2 \tag{6}$$

$$\text{cov}(a_1, a_2) = 0 \tag{7}$$

$$\text{cov}(a_1, S_2) = 0 \tag{8}$$

where a_i, *N*, and S_2 are as defined earlier and *X* is a vector of explanatory variables in structural equation (1). A special case of the MIS represented in equations (3)–(8) is the measurement error problem. In the classical errors-in-variables setup, S_1 and S_2 are the observed error-ridden measurements of *N*, $\pi_0=0$ and $\theta_0=0$, and a_1 and a_2 are the measurement errors in S_1 and S_2, respectively.

The explanations of the MIS conditions (5)–(8) are as follows: (i) equation (5) imposes the exogeneity of *N* and ensures its identification in equations (3) and (4); (ii) equation (6) imposes that the vector of explanatory variables in structural equation (1) is strictly exogenous, i.e., uncorrelated with both the structural and reduced-form equation error terms; (iii) equation (7) indicates that the correlation between indicators S_1 and S_2 arises only through their common dependence on *N* and not through a common error; and (iv) equation (8) follows from equations (5) and (7). Following from MIS conditions (5)–(8) and the standard IV requirement that indicators S_1 and S_2 are correlated, which can be tested via a reduced-form equation, indicator S_2 is a valid

[23] Since school resources are positive the appropriate assumptions for this research are $\pi_1>0$ and $\theta_1>0$, however $\pi_1\neq0$ and $\theta_1\neq0$ are the general assumptions.

instrument for indicator S_1. Since N is unobserved, MIS conditions (5) and (6) cannot be tested while conditions (7) and (8) are satisfied in this application through: (a) invalidation of spending indicators that are correlated through their common components as instruments for each other, e.g., instruction spending as an invalid instrument for total spending or vice versa; (b) use of an instrument that satisfies the exclusion restrictions in all specifications, e.g., the administrative staff-student ratio as an instrument; and (c) whenever possible, preference is given to real resources as instruments for financial resources, and vice versa, given that their error terms are less likely to be correlated[24].

The reduced-form equation for the endogenous school resource indicator is:

$$S_{1i,t-1} = \phi + \rho_j I_{ji} + \zeta_k F_{kit} + \mu_m H_{mi} + \pi_n S_{2i,t-1} + \psi_q X_{qit} + \varepsilon_{it} \tag{9}$$

where I_{ji}, F_{kit}, $H_{mi,}$ and X_{qit} are as defined earlier, and the error term ε_{it} is assumed to be identically and independently normally distributed (iid). The dependent variable, $S_{1i,t-1}$, is the endogenous resource indicator instrumented by a single, redundant indicator, $S_{2i,t-1}$. The estimated parameter π_n provides a test statistic (H_o: $\pi_n=0$) for the identification of structural equation (1) as well as the validity of $S_{2i,t-1}$ as an instrument for $S_{1i,t-1}$.

So far, two IV estimators have been discussed using related procedures: the two-step and standard maximum likelihood (ML) estimators. The two-step IV estimators were obtained through a first-step estimation of the reduced-form equation and prediction of the school resource indicator $S_{1i,t-1}$ using ordinary least squares (OLS) and a second-step estimation of the structural equation that utilizes the first-step predicted values of $S_{1i,t-1}$. In the standard maximum likelihood estimation (MLE) procedure, equations (1) and (9) were estimated simultaneously. Since the second-step estimation of structural equation (1) in the two-step procedure ignores the error term ε_{it} in the reduced-form equation (9), this procedure obtains standard errors and test statistics that are invalid. Given this condition, the standard ML estimators are preferred to the two-step IV estimators: $IV_{2\text{-}step} < IV_{MLE}$. A third IV estimator that incorporates time-constant unobserved heterogeneity is discussed next.

[24] For instance, financial resource indicators are reported by a University's Accounting Office while real resource indicators are reported by its Administrative Office.

1.4.3. Time-Constant Unobserved Heterogeneity

In the baseline random-effects probit methodology, the basic assumption of random fixed-effects was imposed. Following Papke and Wooldridge (2008), an explicit function of the time-constant unobserved heterogeneity can be incorporated into the empirical model to relax this restrictive assumption using an ML technique ($IV_{Papke\ and\ Wooldridge}$). In essence, the time-constant unobserved heterogeneity is assumed to be correlated with the time-varying explanatory variables in some manner. Adding fixed effects, m_i, in the analysis transforms equations (1) and (2) above into:

$$E(CA_{it} \mid I_{ji}, F_{it}, H_{mi}, S_{1i,t-1}, X_{qit}) = G(\alpha + \beta_j I_{ji} + \chi_k F_{kit} + \delta_m H_{mi} + \lambda_n S_{1i,t-1} + \gamma_q X_{qit} + m_i + v_{it}) \tag{10}$$

and

$$CA^*_{it} = \alpha + \beta_j I_{ji} + \chi_k F_{kit} + \delta_m H_{mi} + \lambda_n S_{1i,t-1} + \gamma_q X_{qit} + m_i + v_{it}, CA = 1(CA^* > 0), \tag{11}$$

where all other parameters and variables are as defined earlier. In this application, m_i can be thought of as the schools attended by siblings or parents, as well as other time-invariant unobserved variables, such as student motivation, that influence a student's school choice. In this case, v_{it} is the time-varying unobserved effect that can be correlated with $S_{1i,t-1}$. Using a conditional normality assumption, as in Chamberlain (1980):

$$m_i \mid U_{i1}, U_{i2}, ..., U_{iT} \sim Normal(\psi + \overline{U}\xi_1, \sigma_b^2) \tag{12}$$

where U is the vector of time-varying explanatory variables in (1) and (10) and $\bar{U}$ is the corresponding time-averages vector of the time-varying explanatory variables, which in turn may be expressed with the following linear equation:

$$m_i = \psi + \xi_1 \overline{U} + b_i. \tag{13}$$

In this case, the properties of the normal distribution in the probit function can conveniently provide computationally simple estimators in the presence of unobserved heterogeneity or endogenous explanatory variables. By utilizing the normality distributions in both equations (10) and (13) and substituting the explicit function of m_i in equation (13) into equation (10), the following transformations of the structural equation are obtained:

$$
\begin{aligned}
&E(CA_{it} \mid I_{ji}, F_{kit}, H_{mi}, S_{it}, X_{qit}, b_i, v_{it}) \\
&= G(\alpha + \beta_j I_{ji} + \chi_k F_{kit} + \delta_m H_{mi} + \lambda_n S_{1i,t-1} + \gamma_q X_{qit} + \xi_1 \overline{U}_i + b_i + v_{it}) && (14) \\
&= G(\alpha + \beta_j I_{ji} + \chi_k F_{kit} + \delta_m H_{mi} + \lambda_n S_{1i,t-1} + \gamma_q X_{qit} + \xi_1 \overline{U}_i + z_{it}) && (15)
\end{aligned}
$$

where $z_{it} = b_i + v_{it}$ and the time-constant unobserved heterogeneity, m_i, is replaced in equation (14) by b_i, which can be assumed to be independent of I_{ji}, F_{it}, H_{mi}, $S_{1i,t-1}$, *and* X_{qit}.

In addition, the Mundlak (1978) device transforms the linear reduced-form equation into:

$$S_{1i,t-1} = \phi + \rho_j I_{ji} + \zeta_k F_{kit} + \mu_m H_{mi} + \pi_n S_{2i,t-1} + \psi_q X_{qit} + \xi_2 \overline{U} + \varepsilon_{it} \quad (16)$$

where the right-hand side variables include $\bar{U}$, a vector of the time averages of the time-varying exogenous explanatory variables in the structural equation.

Finally, the school resource endogeneity in equation (15) arises from the correlation between z_{it} (= $b_i + v_{it}$) and ε_{it} in equation (16), i.e., the school resource indicators can be correlated with both the time-constant and time-varying unobserved effects, which can be represented by:

$$z_{it} = \kappa\varepsilon_{it} + r_{it} \quad (17)$$

where

$$r_{it} \mid \varepsilon_{it}, I_{ji}, F_{kit}, H_{mi}, X_{qit} \sim Normal(0, \sigma_r^2). \quad (18)$$

The conditional normal assumption in equation (18) and a standard mixing property of the normal distribution (Wooldridge, 2010) permits the identification of $S_{1i,t-1}$ in the following control function, suitable for estimation using the maximum likelihood technique:

$$
\begin{aligned}
&E(CA_{it} \mid I_{ji}, F_{kit}, H_{mi}, S_{1i,t-1}, X_{qit}, b_i, v_{it}) \\
&= G(\alpha_r + \beta_{rj} I_{ji} + \chi_{rk} F_{kit} + \delta_{rm} H_{mi} + \lambda_{rn} S_{1i,t-1} + \gamma_{rq} X_{qit} + \xi_{r1} \overline{U}_i + \kappa_r \varepsilon_{it}) && (19)
\end{aligned}
$$

where the subscript r denotes division by

$$(1+\sigma_r^2)^{1/2} \quad (20)$$

to obtain the scaled estimated coefficients α, β_j, χ_k, δ_m, λ_n, γ_q, and ξ_1.

Overall, the random-effects probit estimators are provided for the attendance decisions while the following four estimators are obtained for the completion probability model: the baseline random-effects probit (RE), the two-step IV ($IV_{2\text{-step}}$), standard MLE IV (IV_{MLE}), and the Papke and Wooldridge (2008) MLE IV ($IV_{\text{Papke and Wooldridge}}$) estimators.

1.5. Results

This section discusses the estimated effects of student background characteristics on college attendance decisions, and as well the effects of school resources on college completion decisions for alternative specifications, definitions of the dependent variables, time windows, and methodologies. The estimated marginal effects in the following discussions were evaluated at the mean of the explanatory variables, unless otherwise specified.

1.5.1. Baseline Random-Effects Probit Estimates: Attendance

Table 3 shows consistent results for the fully specified attendance probability model estimates using the three time windows of 1982–1985, 1983–1986, and 1984–1987 (columns 4, 8, and 12). Based on a likelihood ratio test, these fully specified models are preferred over the simpler specifications that include only a single category for student background characteristics in the estimations (columns 1–3, 5–7, and 9–11). The results indicate that individuals with higher ability and precollege achievement, who have never been married, and who have more educated parents have a higher probability of attending college, while the male and white segments of the population have lower college attendance probabilities by about 1 and 3.5–6 percentage points, respectively.

More precisely, a one-standard deviation increase in the ASVAB test score, an individual who has never been married, and a one-point increase in high school GPA are estimated to raise the probability of college attendance by 2.6–3.7, 2.6–3.9, and 1.8–3.3 percentage points, respectively. Although more educated parents are also expected to have positive and statistically significant effects on the college attendance probabilities of their children, the economic significance of the estimates are quite low, i.e., a one-grade increase in either parent's education is estimated to raise probability of college attendance by 0–0.3 percentage points.

<Table 3> about here

Next, I discuss the impact on the estimation results of the adjustment of the definition of the college attendance dependent variable of assigning a value of 1 for the first year of a window for cross-sectional observations that completed grade 13 prior to the observed time period. The idea behind the definition adjustment is to incorporate in the estimations the achievement experiences of students that started college prior to the time windows.

As the results in Table 4 show, the estimation results using the adjusted attendance definition and the 1982–1985 window (column 1) are similar to those of the unadjusted attendance definition and the 1979–1982 window (column 2) when survey respondents were closer to the traditional college-going ages of 18–22. Meanwhile, the estimates for the unadjusted attendance dependent variable definition and the 1982–1985 window (column 3) yield statistically insignificant estimated coefficients, or lower marginal effects, for otherwise statistically significant estimated coefficients. Specifically, gender is statistically insignificant in column 3 while the estimated marginal effects for ability, race, marital status, and high school GPA are about 50 percent of those in columns 1 and 2. Overall, these statistically insignificant estimators and muted estimated marginal effects imply that failure to make the suggested definition adjustment on attendance will yield estimators that reflect only the causal behavior of those who started college within the time windows.

<Table 4> about here

1.5.2. <u>Baseline Random-Effects Probit Estimates: Completion</u>

In addition to individual, family, and environmental characteristics, the impact of school resources on student completion was also explored. Columns (1)–(10) in Table 5 present the random-effects estimates from the simpler specifications, while columns (11)–(16) report the results from the full specifications. Based on a likelihood ratio test, the fully specified empirical models that include both the student background and school characteristics as explanatory variables are preferred over their simpler counterparts.

Besides research spending, the fully specified models reveal positive and statistically significant school resource effects. More precisely, the estimated marginal effect for the faculty-student ratio indicates that a one-hundredth of a point increase in faculty-student ratio can raise the probability of college completion by about 3 percentage points, while a 10 percent increase in instruction, academic-related, financial aid, or total per-student spending are estimated to raise college completion probability by about 2 percentage points.

Among student background characteristics, ability, race, and high school GPA are found to have positive and statistically significant effects on completion. The estimated marginal effects indicate that a one-standard deviation increase in the ASVAB test score, being white, and a one-point increase in high school GPA can raise the probability of college completion by 7.5–9.5, 9.4–11.4, and 20.9–22.9 points, respectively.

<Table 5 about here>

Using the same logic provided in the college attendance case, the binary college completion dependent variable was also adjusted for respondents who finished college prior to the time windows by assigning these observations a college completion dependent variable equal to 1 on the first year of the window. Similar to the results obtained in the attendance case, the results using an unadjusted completion definition yield statistically insignificant estimated coefficients for otherwise statistically significant estimated coefficients and muted estimated marginal effects. The bottom section of Table 6 reports more student characteristics with statistically significant estimated coefficients for the specification with the adjusted definition (column 1), such as ability, race, and high school GPA. Except for a few cases, only high school GPA had a statistically significant estimated coefficient for the unadjusted college completion definition (column 2). In addition, the estimated marginal effects for the school resource indicators are lower by at least 40 percent for instruction, academic-related, and total spending in specifications that use the unadjusted completion dependent variable.[25] These results indicate that in general, failure to account for the achievement of the group who completed college prior to the time windows would provide downward-biased student background characteristics and school resources estimators.

<Table 6> about here

To examine the sensitivity of the baseline estimates to variations in the time windows, random-effects probit estimators were also obtained for two alternative time periods, 1985–1988 and 1986–1989. Table 7 reveals that the results are not sensitive to the period under consideration. The school resource marginal effect estimators are comparable across the three time windows, with particularly similar estimated marginal effects for the faculty-student ratio, financial aid, and total spending.

[25] However, the differences in the estimated coefficients are much smaller for the faculty-student ratio and financial aid spending.

<Table 7 about here>

Finally, I also added age and year dummy interaction terms in the baseline specification to explore whether the age variation among respondents, more specifically the behavior of a relatively older group, is driving the estimation results. For instance, survey respondents might have had a longer college career simply because they were older. Adding these interaction terms yields estimated school resource marginal effects that are marginally lower, by 0.6–0.8 percentage points, but that remain statistically significant.

1.5.3. <u>Omitted Variable Bias and Overestimated Ability Coefficients: Completion</u>

One of the contributions of this paper to the growing higher education achievement literature is the joint estimation of the relative impacts of student background characteristics and school resources on college completion through a merged dataset. Table 8 reveals that in addition to an estimation of the impact of school resources on student achievement, the merged dataset also plausibly provides more accurate estimates of ability effects on college completion.

If it is assumed that either high-ability students sort into resource-rich, high-spending schools, or resource-rich, high-spending schools select high-ability students from its applicant pool (Light, 2000), then it can be expected that a college completion specification that omits school resources will yield overestimated ability coefficients by confounding the role of ability and school resources on completion. Table 8 reports the baseline random-effects probit ability estimators of college completion specifications that omit (column 1) and control for different school resources (columns 2–7) across three windows. Based on a Hausman test, the overestimated ability coefficients in specifications that omit school resources are statistically significant except for two cases, namely controlling for the faculty-student ratio and research spending for the 1986–1989 window. This evidence is consistent with the school quality-student ability matching view.

<Table 8 about here>

1.5.4. <u>Reduced-Form Equations and Valid Instruments: Completion</u>

Table 9 presents the results from estimating the reduced-form MIS equations. Overall, the results presented reveal that the school resource indicators satisfy the basic IV requirement of correlation between the instrument and the endogenous variable. In addition, Newey's (1985) overidentification test reveals that all potential instruments are exogenous.

<Table 9 about here>

Under the MIS conditions outlined earlier, however, real and financial resource indicators that are components of each other are invalid instruments, i.e., faculty-student and administrative-staff-student ratios; instruction, academic-related, and total spending; research, academic-related, and total spending; and financial aid and total spending. These combination of resource indicators were therefore dropped from the analysis. Finally, valid instruments are obtained if the Wald test indicates the endogeneity of the school resource indicator in the structural equation conditioned on a specific resource instrument. Table 10 presents the Wald tests for the two-step estimations and identifies the valid ML instruments using shading. For example, among instruments that satisfy the MIS conditions for instruction spending, the two-step IV Wald test identifies the faculty-student and administrative staff-student ratios, and financial aid spending as valid instruments, while the MLE IV Wald test identifies financial aid spending as the only valid instrument. Finally, for comparative purposes across IV methods, only valid instruments from the standard ML estimations were considered in the Papke and Wooldridge ML IV estimations. Table 11 provides a list of valid instruments for each IV procedure.

<Tables 10 and 11 about here>

1.5.5. Instrumental Variable Estimates: Completion

Table 12 reports two random-effects probit estimators and three IV estimators for the school resource indicators, including the instruments used for all IV specifications. For the random-effects probit estimates, column 1 replicates the results from the baseline specification, while column 2 shows the results from a specification that incorporates time-constant unobserved heterogeneity through inclusion of the averages of household income and the local labor market unemployment rate as explanatory variables.[26] The small variation in both the estimated coefficients and the marginal effects for the school resource indicators between these two random-effects probit specifications implies that time-constant unobserved heterogeneity does not cause a

[26] The average of the school resource indicator was not included as an explanatory variable because of limited time-series variation within the cross-sectional observations.

serious problem in the estimations since it has most likely been accounted for by the exhaustive covariates used in the baseline analysis or by the random-effects estimation technique.

For the three IV estimators, the minimum estimated marginal effects for both the two-step and standard ML procedures are reported in columns 3 and 5. The maximum estimated marginal effects for all three IV procedures are also reported in columns 4, 6, and 7, including the Papke and Wooldridge ML and the instruments used. All the IV estimators reported in columns 3–7 are based on valid instruments that were identified using the three-point criteria outlined above.

In relation to the baseline estimators, the IV estimators are significantly higher for all six school resource indicators, including the estimated coefficient on research spending that becomes statistically significant in all three IV estimations. Additionally, the estimated marginal effects from all three IV procedures are generally similar. For the faculty-student ratio, the corresponding estimated marginal effect across the three IV specifications is 22–36 percentage points, and for academic-related spending is 3–5 percentage points. However, a preferred IV method can be revealed by a process of elimination based on statistical tests.

First, based on likelihood ratio tests and Wald tests that identify school resource indicators as endogenous, all three IV procedures are preferred over the baseline random-effects probit estimation. Second, since the two-step estimators provide invalid standard errors and statistical tests, the two ML IV estimators (standard and Papke and Wooldridge) are the preferred IV estimators. Lastly, based on likelihood ratio tests, the Papke and Wooldridge ML is preferred over the standard ML specification. Hence, the preference ordering for the four estimation procedures is as follows: $RE_{probit} < IV_{two\text{-}step} < IV_{standard\ ML} < IV_{Papke\ and\ Wooldridge\ ML}$. Naturally, in cases when no valid instruments can be identified for the Papke and Wooldridge ML procedure, the second-best estimation procedure that yields a valid instrument substitutes as the preferred method.

Based on the Papke and Wooldridge ML estimators in Table 12 column 7, a one-hundredth percentage of a point increase in, or equivalently a doubling of, the faculty-student ratio can raise college completion probability by about 36 points, while a 10 percent increase in per-student instruction, research, or academic-related spending is estimated to each raise completion probability by about 3.5 points. Using the standard IV ML estimates for financial aid spending and the two-step estimates for total spending, the corresponding marginal effects of these two spending categories is about 2.5 points.

<Table 12> about here

Finally, due to the large number of missing observations for the school resource indicators, so that the estimated IV marginal effects evaluated at the mean plausibly capture the impact of school resources at the lower-tail of the school resource distribution, I also calculated the estimated marginal effects at different percentiles, i.e., the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles, of the actual school resource distribution.[27] Interestingly, the results in Table 13 reveal that only research and financial aid spending have positive and statistically significant but diminishing effects on student completion through all points of the corresponding resource distribution. The positive and statistically significant effects of the faculty-student ratio, and academic-related and total spending disappear beyond the 25th percentile and for instruction spending after the 10th percentile of the corresponding resource distribution.

<Table 13 about here>

1.6. Conclusion and Discussion

In this paper, I investigated the impact of student background characteristics and school resources on college attendance and completion. Due to data availability issues, the existing literature provides limited estimates of the impact of school resources on student achievement using the standard education production function framework. Through a merged dataset of the NLSY79 Geocode version and IPEDS, the results obtained demonstrate that less-than-fully specified models that treat student background characteristics and school resources separately in college completion specifications will lead to overestimated ability coefficients. Moreover, I find evidence that school resources are endogenous and therefore possibly influenced, among others, by budget-related decisions of school administrators and state officials, peer characteristics, and evolving student motivation.

The attendance models revealed that ability, having never been married, and precollege preparation increase an individual's likelihood of going to college. Although both father's and mother's education are also estimated to have positive impacts on attendance, their expected

[27] The actual school resource distribution ignores the missing values that have been identified with the missing indicators.

effects are arguably of little economic significance. Finally, male and white segments of the population are less likely to attend college.

In contrast, the white segment of the population is more likely to graduate by 7–10 percentage points, while an excellent high school record greatly increases a student's chances of completion by as much as 20 percentage points for each 1-point rise in high school GPA. Although past studies (Dynarski [2002, 2003] and Bound and Turner [2007]) that evaluated the average impact of a change in resources on student achievement found a positive causal link, a more detailed investigation across the resource distribution reveals that school resources matter in influencing student completion mostly in low-resource institutions. Similar to Bound and Turner (2007), who found that a 10 percent increase in the college-age cohort size reduces college attainment by 4 percentage points, I find that an overall decline in per-student spending reduces college attainment by about 3 percentage points on average and by as much as 10 percentage points for students who attend very low-spending schools.

Among resource indicators, the positive influence of the faculty-student ratio, and instruction, academic-related, and total spending on the completion probability generally disappears beyond the 25th percentile of the resource distribution. Although research and financial aid spending influence completion at all points of their respective resource distributions, the marginal effect of increased spending is also greater at the lower-tail of the distribution for financial aid and at the median for research spending. To put this into perspective, a $1,000 increase in aid raises the completion probability by about 50 percentage points for students receiving amounts that are at the 50th percentile of the aid distribution, but only by about 5 percentage points for those already receiving aid equivalent to the 95th percentile of the distribution.

The results imply that, at least for NLSY79 respondents or a cohort of young men and women aged 14–22 in 1979, precollege achievement significantly influences both college attendance and completion, while school resources generally impact the completion of students only at low-spending institutions. Despite the important implications revealed by this study relating to college success, the limitations of the data and the econometric method must be underscored. Since the NLSY79 was not explicitly designed to follow students during their college careers, it is highly likely that I am capturing variation among a very select number of observations.

Hence, for future studies, more appropriate longitudinal surveys, such as the High School and Beyond Survey or the National Education Longitudinal Study, might provide additional insights. If available, more recent surveys could also reveal current trends in resource impacts. Finally, the restrictive functional form assignment on the structural equations in parametric estimations could be relaxed by using relatively more flexible semiparametric techniques, such as single-index modeling or the median regression model discussed in Horowitz and Savin (2001).

CHAPTER 2. COLLEGE RESOURCES AND STUDENT PERSISTENCE

2.1. Introduction

In this chapter, I extend the analysis on the influence of student background characteristics and school resources on college outcomes, particularly student persistence, using the same data and methods I utilized in Chapter 1. Since the realization of the pecuniary and nonpecuniary returns to a college education hinges on the ability of students to stay through a lengthy college career, the factors that influence college persistence is an important issue that needs to be explored. While there is abundant research on the factors that affect college attendance, retention, and completion, the same attention has not been attributed to persistence. As opposed to student retention, defined as the continuous attendance in the same institution, which is an issue of concern mostly to school administrators whose main goal is to keep progressing, revenue-generating students, persistence follows student progress, or success, through college regardless of which institution the student attends. In this research, I investigate persistence by following a student's repeated, annual decision to complete an additional year of schooling in college from first year to degree completion. More precisely, student persistence is defined as a one-grade increase in completed years of schooling from grades 13 through 16.

It can be argued that a student deciding whether or not to remain in the same institution throughout a college career is not necessarily a manifestation of a problem but rather is the representation of a solution to a mismatch between student and school characteristics that, in turn, could raise overall student completion in the long-run. This rationale puts into perspective the significance of stagnant retention amidst falling persistence rates over the last few years among full-time students who started college in four-year institutions, implying a phenomenon in which a growing proportion of students who had chosen to leave their institution either dropout or stopout from college. In public four-year institutions, the full-time, first-year retention rate increased slightly from 77.9 percent for the Fall 2009 entering cohort to 78.1 percent for the Fall 2013 entering cohort but the persistence rate decreased through both cohorts by about one percentage point from 87.7 to 86.4 percent. The scenario is very similar among four-year not-for-profit private institutions, wherein retention rate held steady at around 74 percent, while persistence rate fell more rapidly by greater than two percentage points from 85.9 to 83.7 percent.[28] The trend for institution-wide retention rate among full-time, first time degree-seeking undergraduates in both public and private not-for-profit four-year institutions has also been stagnant at about 80 percent since the 2009-2010 academic year, which is monotonically increasing with school selectivity.[29,30]

Overall, the empirical evidence from this research suggest that: (1) failure to estimate a fully-specified education production function results in ability estimator bias; (2) among student background characteristics, ability, precollege preparation, and having never been married raise the probability of student persistence in college; and (3) school resources generally matter only in low-resource institutions with the exception of financial aid for which a 10 percent increase is estimated to raise the probability of student persistence by 0.6-3.4 percentage points for both low- and high-spending institutions.

2.2. Literature Review

Student persistence and retention in college have been defined in the student achievement literature in different ways. These two related student outcomes have been measured in terms of completion of the freshman year, progress from the first year to the second year of college, time to graduation, continuous college attendance from entry to completion in which limited nonconsecutive attendance were also allowed, reenrollment decisions, attrition behavior, and completed years of schooling.

Although the importance of student background and institutional characteristics in influencing both student persistence and retention is widely established in the student achievement literature, very limited research has explored the association between school resources and student persistence. It has been consistently shown that race, gender, precollege achievement, family income and parents' education (collectively, socioeconomic status), and educational aspirations or goals influence student reenrollment decisions. From the institution's standpoint, structural

[28] Data were obtained from the National Student Clearinghouse Research Center. For more information, see http://nscresearchcenter.org/snapshotreport-persistenceretention18/.

[29] 2014. Digest of Education Statistics. Table 326.30. https://nces.ed.gov/programs/digest/d14/tables/dt14_326.30.asp.

[30] For four-year public institutions, 2012-2013 retention rate for schools who accepted 90 or more, 50.0 to 74.9, and less than 25 percent of applications are 71.1, 81.3, and 94.5 percent, respectively. The corresponding figures for four-year not-for-profit institutions are 69.0, 78.7, and 96.6 percent, respectively.

characteristics such as size, control, selectivity, spending, and financial aid awards were found to contribute to college success.

Using Hierarchical Generalized Linear Model, Oseguera and Rhee (2009) found that the following student-level characteristics increase the likelihood of degree completion within six years of attendance[31]: high school GPA, SAT composite score, socioeconomic status, Asian background, and living on campus. In contrast, they find Hispanic ethnicity, financial concern, and precollege expectation of a college transfer negatively impact retention decisions. Among community college students who transfer to four-year institutions to pursue a bachelor's degree, Wang (2009)[32] identified GPA at the community college as a significant predictor of persistence, while gender, socioeconomic status, high school curriculum track, baccalaureate aspirations, involvement in college extracurricular activities, and GPA at the community college were shown to be associated with four-year degree attainment. Lotkowski, Robbins, and Noeth (2004) found a moderate to strong influence of the academic factors of high school GPA and ACT test score as well as socioeconomic status on student retention and college GPA. Finally, Ishitani (2006) showed that first-generation students, lower family income, lower high school achievement and program quality, discontinuous college attendance, and attendance at public and less selective four-year institutions contribute to higher student attrition and lower likelihood of timely graduation with varying relative impacts over time.

In the economics literature, Light (1995) demonstrated through a semiparametric proportional hazard model that the likelihood of reenrollment among young men is positively related to individual characteristics such as ability, age, race, and having never married, while those that face higher opportunity costs of reenrollment, i.e., higher tuition levels, hold high-paying, full-time jobs, and lower local unemployment rates, are less likely to reenroll. In addition, her research identified the existence of a liquidity constraint whereby the young men who left school and eventually returned to college had to work fairly continuously to either finance or appreciate the value of additional schooling.

[31] Alternatively, they defined retention as attendance at the same institution over a six-year period.

[32] Wang (2009) used the logit regression technique and data from the National Education Longitudinal Study of 1988 and Postsecondary Education Transcript Study. Persistence in this research was defined as continuous attendance of no more than a semester or two quarters of break while completion was defined as bachelor's degree attainment by the year 2000.

The research on the impact of school resources on student retention focus mainly on financial aid and tuition levels. Using random variation in financial aid arising from the end of the Social Security Benefit Program in 1981, Dynarski (2003) estimated that student aid eligibility[33] increased the probability of completing at least a year of college by about 14.5 percentage points and years of completed schooling by about half a year. In an investigation of the impact of financial aid across income groups, Chen and DesJardins (2008) found that Pell grants effectively supplement parental income among low-income students, while loans and work-study programs have similar effects on dropout behavior across all income groups. Ishitani (2008) found that access to grants and work-study programs decrease student attrition and increase likelihood of degree completion while loans have the opposite effect. Finally, higher tuition levels were shown to deter young men from reenrollment (Light 1995).

Another strand of the education literature on postsecondary student achievement highlights the role that psychological factors, peer influence, and college experience play in the college success of students. For instance, Wang (2008) found that a community college transfer student with an internal locus of control perception is more likely to stay through four years of college, while baccalaureate aspirations and college involvement increase the likelihood of completion. Oseguera and Rhee (2009) meanwhile emphasize peer characteristics and institutional climate as important determinants of student retention. In particular, they find colleges that are more selective, have higher average student quality, and lower dropout and transfer precollege intentions among students contribute to higher student retention. In Lotkowski, Robbins, and Noeth (2004), institutional commitment, academic goals, social support, academic self-confidence, and social involvement were found to be linked to college retention, while academic self-confidence and achievement motivation were shown to have strong influence on college GPA.

2.3. Data and Empirical Methodology

Since I utilize the same data and methodology as in Chapter 1, I provide only the summary here. The merged NLSY79 Geocode and IPEDS data, linked through the schools attended by NLSY79 respondents reported using FICE and IPEDS codes in the NLSY79 Geocode version, is used to

[33] The 1980 average annual payment to the child of a deceased parent was $6,700.

examine the causal link from student characteristics and school resources to student persistence. The random-effects probit methodology will provide the baseline estimates.

Since the school choice decision is subject to self-selection bias through variation in, among others, student and family characteristics, and academic motivation and goals, and school resources are subject to the budget allocation decisions of school administrators and policymakers that are dependent on their shifting goals and objectives, I once again utilize the multiple indicator solution variant of the instrumental variables methodology to account for the endogeneity in the school resource indicators. Three IV estimators are presented using the following techniques: two-step, standard Maximum Likelihood (ML), and the Papke and Wooldridge (2008) Maximum Likelihood. Besides accounting for the endogeneity issue, the Pakpe and Wooldridge ML method also introduces the time-constant unobserved heterogeneity in the empirical model by implementing the Chamberlain (1980) and Mundlak (1978) devices through the standard normal distribution function assumed in the random-effects probit estimation technique. The reduced-form and structural equations (1) and (2) in Chapter 1 are similar, except for the dependent variable and the length of time windows that will be discussed in the following sections. Similar to Ram (2004), Papke (2005) and Roy (2011), the school resource indicators are also introduced in the student persistence specifications as one-year lagged explanatory variables.

2.3.1. Setting Time Windows

Since college persistence is a multiple-decision process potentially spanning a student's four-year college career, if not more, and that 150 percent of normal time graduation rate among the 1996 to 2006 cohorts of first-time, full-time, bachelor's degree-seeking students attending their first four-year postsecondary institutions is between 55-60 percent[34], I follow the persistence decisions for six years of the group of NLSY79 respondents who went to college. To obtain an idea on the robustness of results, I also consider three time windows, 1984-1989, 1985-1990, and 1986-1991, when the NLSY79 respondents were aged 19-27, 20-28, and 21-29 on the first year of each window, respectively. Although earlier time periods when more respondents approximate the traditional college-going ages of 18-22 would have been more appropriate, this type of analysis is

[34] 2015. Digest of Education Statistics 2014. National Center for Education Statistics.

limited by NLSY79 data availability which started collecting school attendance history only in 1984.

2.3.2. <u>Definition of the Binary Persistence Dependent Variable</u>

College persistence is a binary dependent variable assigned a value of 1 for the year if the NLSY79 respondent reported a one-grade progress in completed schooling during the current year, with the condition of completion of grade 13, 14, or, 15 in the previous year, and 0 otherwise. Hence, only respondents who reached grades 13 through 15 are part of the analysis while those who completed grade 16 for the current year would drop out of the sample in the succeeding year. To test the robustness of the results, baseline estimators were also obtained for three alternative definitions of the binary persistence dependent variable: progress from grades 13 to 14, 14 to 15, and 13 to 15 with the condition of, respectively, completing grades 13, 14, and 13 or 14 in the preceding year.

2.3.3. <u>Descriptive Statistics</u>

Table 14 presents the summary statistics (means and standard deviations) of the explanatory variables used in the college persistence probability estimation for the entire sample (column 1) as well as separately for persisters (column 2) and nonpersisters (column 3). Among the 14,546 observations that completed at least grade 13 in 1984-1989, 21.7 percent (3,151) went on to complete a higher grade level. Consistently, persisters attend institutions with more resources, i.e., higher faculty-student ratio and per-student spending. In particular, persisters in the sample attend institutions that spend at least five times more than the schools attended by nonpersisters. Among student background characteristics, students who went on to progress to a higher grade level can also be distinguished by higher standardized test scores (0.61 versus 0.21), a greater proportion who never married (0.81 versus 0.49), better high school GPA (2.50 versus 2.13), and more educated parents (father’s education of 12.04 versus 11.12 and mother’s education of 12.04 versus 10.46).

<Table 14> about here

2.4. Results

This section discusses the estimated effects of student background characteristics and school resources on college persistence decisions for alternative specifications, definitions of dependent variables, time windows, and methodologies. The estimated marginal effects in the following discussions were evaluated at the mean of the explanatory variables, unless otherwise specified.

2.4.1. <u>Baseline Random-Effects Probit Estimates: Persistence</u>

Table 15 reports the results from the baseline random-effects probit estimations. Based on a likelihood ratio test, the fully-specified models in columns (11)-(16) that jointly incorporate student background and resource characteristics in the analysis are preferred over the less-than-fully-specified empirical models in columns (1)-(10). Although the six school resource indicators are estimated to have positive and statistically significant effects on student persistence, the marginal effects are arguably of minimal economic significance. For instance, a 10 percent increase in any of the five per-student spending categories is estimated to lead to less than 1 percentage point rise in the probability of student persistence, i.e., 0.7, 0.6, 0.5, and 0.1 of a percentage point, respectively, for each of instruction and total, academic-related, financial aid, and research per-student spending.

Among student background characteristics, ability, never married status, precollege preparation, and father's education each have positive and statistically significant influences on student persistence. The marginal effects of ability, never being married, and high school achievement are particularly strong: an increase of one-standard deviation in the ASVAB standardized test score and one-point rise in high school GPA are expected to raise the probability of reenrollment at any institution for the following year by 4-7, 5-8, and 4.5-6.5 percentage points, respectively. On the other hand, an additional completed grade of education by the father is estimated to cause an increase in persistence probability by less than 1 percentage of a point. On the demand side, a 10 percent increase in household income reduces persistence probability by 1.5-2 percentage points.

<Table 15> about here

To test the robustness of the baseline results, I also explored alternative definitions of the persistence dependent variable. Table 16 replicates the results of estimations using the grade 13 to

16 persistence definition in column 1 as well as reports the estimation results that define the dependent binary persistence dependent variable as progress from grades 13 to 15 (column 2), 13 to 14 (column 3), and 14 to 15 (column 4). Evidently, the school resource marginal effects are very similar across the four definitions of student persistence but greater resources appear to have a marginally greater impact in facilitating student progress from the sophomore to the junior year (grade 14 to 15) than from the freshman to the sophomore year (grade 13 to 14), i.e., a 10 percent increase in instruction, academic-related, financial aid, and total spending are each estimated to raise probability of student persistence from grade 13 to 14 by 0.7, 0.6, 0.4, and 0.6 of a percentage point, respectively, while the equivalent estimates for progress from grade 14 to 15 are 1, 0.9, 0.8, and 1. Similar student background characteristics were also found to influence student persistence across the four definitions of the binary dependent variable: in general, ability, never married status, and precollege preparation were found to have positive and statistically significant effects on college persistence, while higher income was estimated to have a negative effect.

<Table 16> about here

In addition to the baseline estimates for the 1984-1989 time window, estimators were also obtained for the 1985-1990 and 1986-1991 time periods (Table 17). The school resource estimators are decreasing over time, which can be attributed to the maturation of the NLSY79 respondents who, by 1986, were aged 21-29 and by then were more likely to be in the later stages of a college career, pursuing graduate education, or participating in the labor market. To illustrate, a 10 percent increase in per-student total spending is estimated to raise probability of student persistence by 0.7 and 0.6 of a percentage point in the 1984-1989 and 1985-1990 time windows, respectively, but only by 0.4 of a percentage point when observing the 1986-1991 time window.

<Table 17> about here

2.4.2. <u>Omitted Variable Bias and Overestimated Ability Coefficients: Persistence</u>

Similar to the student completion analysis, less than fully-specified models that do not control for school resources also predict higher ability marginal effects on student persistence (Table 18 column 1) than fully-specified models (columns 2-7). Based on a Hausman test, the differences in the estimated coefficients between the fully-specified and less than fully-specified models are statistically significant at the 1 percent level across all school resource indicators and time windows. For the 1984-1989 time window, it is estimated that a one-standard deviation increase in the ASVAB test score can raise student persistence probability 0.9 percentage of a point in less than fully-specified models but only by 0.4-0.7 percentage of a point in the fully-specified models. These results lend further support to the argument that high ability students who progress through college are more likely to attend high-resource institutions or that high-resource, high-quality institutions are more likely to pick high-ability students from their pool of applicants.

<Table 18> about here

2.4.3. Instrumental Variable Estimates: Persistence

Table 19 presents the results from estimating the reduced-form MIS equations which reveal that the school indicators satisfy the basic IV requirement of correlation between the instrument and the endogenous variable. Based on the MIS conditions discussed in detail in Chapter 1, I consider the financial indicators that are components of each other to be invalid instruments, i.e., instruction and academic-related spending.

<Table 19> about here

As a third criteria in choosing the valid instruments, the Wald test was also used to identify those instruments for which the resource indicators were identified as endogenous in the structural equation conditioned on a specific instrument. Among the school resource indicators that satisfy these three criteria, the Newey (1995) overidentification tests further reveal that the redundant instruments are exogenous in all the student persistence structural equations.[35] Table 20 presents the results of the Wald test for which the null hypothesis is all resource indicators are not endogenous in a two-step estimation procedure and identifies the valid ML instruments using shading. For example, if any of the spending indicators is used as an instrument, the Wald test null hypothesis that the faculty-student ratio is not endogenous can be rejected in both the two-step and standard ML estimation procedures but only rejected in the two-step estimation procedure if the administrative staff-student ratio is used as the instrument. Since the results of the Wald tests generally indicate endogeneity of school resources, the multiple indicator solution variant of the

[35] The results of the overidentification tests are available from the author upon request.

instrumental variables methodology is utilized to identify the resource effects on student persistence.

<Table 20> about here

Table 21 provides a list of valid instruments for the three IV estimation procedures. In cases that a valid instrument cannot be identified for a resource indicator, the second-best IV procedure that yields a valid instrument substitutes as the preferred method, e.g., for financial aid spending, the estimated marginal effect is obtained from the standard ML estimations. Since the bias of two-stage least squares estimators is approximately zero in the just-identified IV specifications in cases of weak instruments and proportionally rises with the degree of overidentification (Angrist and Krueger, 2001), I only report and discuss the just-identified IV estimators. In this application, however, the potential overidentification bias does not appear to be an issue since the predicted marginal effects for the overidentified two-step IV specifications[36] fall between the minimum and maximum predicted marginal effects for the just-identified specifications.

<Table 21> about here

Table 22 reports two random-effects probit estimators and three IV estimators for the school resource indicators, including the instruments used for all IV specifications. For the random-effects probit estimates, column 1 replicates the results from the baseline specification, while column 2 shows the results from a specification that incorporates time-constant unobserved heterogeneity through inclusion of the averages of household income and the local labor market unemployment rate as explanatory variables.[37] The small variation in both the estimated coefficients and the marginal effects for the school resource indicators between these two random-effects probit specifications implies that time-constant unobserved heterogeneity does not cause a serious problem in the estimations since it has most likely been accounted for by the exhaustive covariates used in the baseline analysis or by the random-effects estimation technique.

For the three IV estimators, the minimum predicted marginal effects for both the two-step and standard ML procedures are reported in columns 3 and 5. The maximum estimated marginal effects for all three IV procedures are also reported in columns 4, 6, and 7, including the Papke

[36] The overidentified two-step IV estimations included all valid instruments in the reduced-form estimations.
[37] The average of the school resource indicator was not included as an explanatory variable because of limited time-series variation within the cross-sectional observations.

and Wooldridge ML and the instruments used. All the IV estimators reported in columns 3–7 are based on valid instruments that were identified using the three-point criteria outlined above.

In relation to the baseline estimators, the IV estimators are significantly higher for all six school resource indicators. Additionally, the predicted marginal effects from the two ML procedures are generally higher than those obtained from the two-step procedure. For the faculty-student ratio, the corresponding predicted marginal effect from the two-step procedure is 11-12 and 25–37 percentage points from the standard and Papke and Wooldridge ML estimations, and for instruction spending the corresponding predicted values are about 1 percentage point and 1.5-3.3 percentage points, respectively. However, a preference ordering for the different estimation techniques can be revealed by a process of elimination based on statistical tests.

First, based on likelihood ratio tests and Wald tests that identify school resource indicators as endogenous, all three IV procedures are preferred over the baseline random-effects probit estimation. Second, since the two-step IV procedure provides invalid standard errors and statistical tests, the two ML techniques that provide comparable school resource estimators are preferred. Lastly, based on likelihood ratio tests, the Papke and Wooldridge ML is preferred over the standard ML specification. Hence, the preference ordering among the alternative methodologies is: $RE_{probit} < IV_{two\text{-}step} < IV_{standard\ ML} < IV_{Papke\ and\ Wooldridge\ ML}$.

Based on the Papke and Wooldridge ML estimators in Table 9 column 7, a one-hundredth percentage of a point increase in, or equivalently a doubling of, the faculty-student ratio can raise college persistence probability by about 37 percentage points, while a 10 percent increase in instruction, research, academic-related, and total per-student spending is estimated to raise the probability of persistence by about 3.3, 3.9, 2.9, and 2.2 percentage points, respectively. For financial aid spending, the standard ML estimator predicts that a 10 percent rise in per-student financial aid spending can raise college persistence probability by about 0.8-1.8 percentage points.

<Table 22> about here

Similar to the college completion case, a large number of observations for the school resource indicators are also missing in the student persistence data, so that the estimated IV marginal effects evaluated at the mean plausibly capture the impact of school resources at the lower-tail of the school resource distribution. To obtain a better picture of the impact of school resources on student persistence in different spending scenarios, I also calculated the estimated marginal effects at different percentiles, i.e., the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles, of the actual school resource distribution.[38] Overall, the results in Table 23 reveal that greater spending can be effective in influencing student persistence in institutions with relatively lower resources. Aside from financial aid spending, the predicted marginal effects of all school resource indicators are generally positive and statistically significant only at or below the 50th percentile of the resource distributions. Although financial aid spending has a positive and statistically significant effect on student persistence, its causal effect is nonmonotonic across the financial aid distribution. The estimates show that the marginal effect of a 10 percent increase in financial aid increases from 0.6 of a percentage point at the 5th percentile of the distribution to 3.4 percentage points at the 75th percentile, and decreasing thereafter to 2.2 percentage points at the 95th percentile.

<Table 23> about here

2.5. Conclusion and Discussion

In this chapter, I utilized a merged dataset and the multiple indicator solution variant of the instrumental variables methodology to examine the impact of student background characteristics and school resources on student persistence in college, defined as a one-grade progress in highest grade completed from grades 13 through 16. The results obtained show that failure to control for school resources in a standard education production framework of student outcomes will lead to overestimated ability coefficients which is supportive of the view that students self-select into schools that match their abilities or schools admit students who are at par with their level of quality (Light and Strayer, 2000). In addition, I also obtained evidence that school resources are endogenous.

Among student characteristics, I find that ability, precollege preparation, and having never been married increase the likelihood of student persistence in college. More precisely, increases of one-standard deviation in the ASVAB test score and one-point in high school GPA as well as having never been married are predicted to each raise the probability of student persistence by 2-4, 2-4, and 3-4.5 percentage points, respectively. In contrast to Light (1995), I find that household income exerts a negative but economically small influence on student persistence. Finally, this

[38] The actual school resource distribution ignores the missing values that have been identified with the missing indicators.

research also suggests that the influence of school resources on college persistence is generally concentrated at very low-resource institutions, with the exception of financial aid spending.

Although financial aid spending positively influences student persistence in both low- and high-aid institutions, increased financial aid was shown to have its greatest impact on the persistence of mid-1980s students who were in the 50^{th} to the 90^{th} percentiles of the financial aid distribution and thus already receiving reasonable amounts of aid, i.e., $350-1,100, in 1984-1989. These financial aid values are arguably nontrivial in comparison to the 1986-1987 average tuition and fee levels at four-year public and private not-for-profit institutions of $1,259 and $5,517, respectively.[39] The estimates imply that an additional $1,000 in aid, equivalent to about $5,000 in current dollars[40], would have raised persistence probability by about 60 percentage points for this group of students. For students receiving financial aid equivalent to the 90^{th} and 95^{th} percentiles of the distribution, an additional $1,000 in financial aid is expected to raise their probability of persistence by 14 and 24 percentage points, respectively. Although these estimates appear to be very high, it must be emphasized that these upper-bound estimates can be as much as 1.5 times higher than the lower-bound estimates. It can also be argued that the students in this scenario have already made personal commitments in pursuing a college education which makes the opportunity cost of exiting very high. Overall, the research evidence suggests that investment on academic infrastructure impact student persistence only at low-spending institutions while greater spending that reduces the cost of attendance can positively influence student persistence, regardless of the financial aid value received.

In future research, individual student characteristics such as personal motivation and educational aspirations may be incorporated in the education production function framework by utilizing the indicators of attitude, expectations, and social activities found in the NLSY79 data, while a student’s college experience and environment that are also likely to influence student persistence decisions cannot be controlled due to the limitations of the merged data. However, inclusion of these potentially time-invariant factors might be questionable given implied evidence

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[39] This computation was based on the assumption that inflation-adjusted average tuition and fee levels have increased by threefold from 1984-1985 to 2014-2015. For more information, see http://trends.collegeboard.org/college-pricing/figures-tables/tuition-fees-room-board-time-unweighted.

[40] This calculation was based on the College Board data that average tuition and fees has increased by almost five-fold and seven-fold at four-year private not-for-profit and public institutions, respectively.

that the time-invariant unobserved heterogeneity has been controlled in the estimations. Finally, since it has been shown that the impact of school resources varies across the resource distributions, it will also be interesting to learn about the variation in the school resource effects across grade levels in college.

CHAPTER 3. COST EFFICIENCY OF AMERICAN COLLEGES AND UNIVERSITIES

3.1. Introduction

The 2008 economic recession and the fragility of the global economy that followed affected the delivery of many basic services, including higher education. For instance, the University of California system had its state funding cut by $900 million between 2008 and 2013, while the University of North Carolina, Chapel Hill experienced four consecutive years of state funding cuts and in the process absorbed a total of approximately $235 million in state funding reductions during the same period. Private colleges and universities were also not immune to the economic downturn. During the peak of the recession in 2008–2009, investment revenue loss for all four-year higher education institutions was $64 billion (Dillow and Snyder, 2013).

Based on research by Deller and Rudnicki (1993), Hanushek (2002) found that additional resources fail to achieve better student outcomes and pointed to the inefficiency of educational institutions as the plausible culprit. According to this rationale, colleges and universities operating with excess costs can keep their output levels unchanged during budget cuts only through reducing the wasteful use of resources, while efficient schools must absorb declines in output levels.

This research offers plausible explanations as to how American colleges and universities may be impacted by economic shocks through budget cuts and reduced tuition or other revenue at the institutional level. Using a translog cost function and the one-step, panel data variant stochastic frontier analysis methodology developed by Battese and Coelli (1995), this paper estimates the US higher education sector's stochastic cost frontier, predicts the cost efficiency of American higher education institutions, and identifies the determinants of inefficiency. The stochastic frontier analysis (SFA) methodology pioneered by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) estimates a production frontier by assuming a composed error term consisting of the random and one-sided, heteroskedastic inefficiency error terms. In this study, the preference for SFA methodology over the deterministic, nonparametric data envelopment analysis (DEA) lies in the strength of SFA to distinctly handle measurement and random errors through the idiosyncratic error term. Since DEA is a deterministic methodology, the potential presence of the aforementioned errors could potentially provide, and be compounded by, unreliable, estimated cost efficiency levels.

In this empirical exercise, I use a 2006–2011 panel dataset of four-year public and private not-for-profit American colleges and universities, primarily granting baccalaureate degrees or above, that are also classified in the 2000 Carnegie Foundation system as Doctoral/Research Universities - Extensive and Intensive (DRUE and DRUI) and Master's Colleges and Universities I and II (MCU-I and MCU-II). The main data source is the Integrated Postsecondary Education Data System (IPEDS) maintained by the National Center for Education Statistics (NCES), while alternative quality indicators were obtained from Profiles of American Colleges 2013 (Barron's, 2012), Forbes Top Colleges 2014, and the 2015 US News and World Report College rankings.

This research fills a few notable gaps that have been overlooked in the literature on efficiency in the US higher education system. First, due to the unavailability of reliable quality indicators, many researchers have ignored school quality in their cost functions and frontier estimations. Using several indicators, I consider the cost differentials related to institutional quality and show that the results are consistent, and likely to be reliable, across indicators. Similar to studies of universities in Canada and the United Kingdom (UK), I also use a more detailed characterization of the inefficiency effects that assumes inefficiency to be a function of an institution's student, staff, and cost share characteristics. As opposed to Glass et al. (2009), this efficiency function allows for a formal testing of the applicability of the theory of comparative advantage to the US higher education system. Lastly, and possibly the most ignored in other studies, I impose price homogeneity conditions on the cost functions.

The main findings of this research suggest that: (1) the average American college or university operates about 30 percent higher than the higher education sector frontier, equivalent to a cost efficiency of about 77 percent; (2) the omitted school quality bias manifests in overestimated public control effects on total costs; (3) the ratios of part-time and undergraduate students aged 25 and over, female instructors, professors, and nonwhite staff positively impact cost inefficiency; (4) instruction cost share and cost inefficiency are negatively related; and (5) research cost share rises with cost inefficiency, but falls slightly for highly research-intensive institutions, with predicted pivot points at about 45–50 percent.

3.2. Literature Review

Research relating to higher education efficiency can be categorized based on four types of efficiency indicators.[41] Technical efficiency measures the optimality of the process through which colleges and universities convert inputs into outputs; allocative or price efficiency evaluates whether the appropriate mix of inputs are being utilized given relative input prices; and economic or overall efficiency is the sum of both the technical and allocative efficiencies. Generally explored in the same research category, scale and scope economies examine whether institutions are operating at increasing, constant, or decreasing economies of scale, with the objective of determining optimal size of operation and the plausibility of decreasing unit costs through multiple output production. Studies relating to scale and scope economies, such as those by Glass, McKillop, and Hyndman (1995) on the UK[42] and Koshal and Koshal (1999) on the US[43], follow the industrial organization work of Baumol, Panzar, and Willig (1982). These efficiency indicators can be quantified using the production, cost, revenue, or profit functions.[44]

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[41] Katharaki and Katharakis (2010) provide a good summary of the types of efficiency.

[42] Glass, McKillop, and Hyndman (1995) utilized cross-sectional data on 61 UK universities, subdivided into three groups based on their research quality scores from the 1989 UK Research Assessment Exercise (RAE). Estimating a three-output, two-input hybrid translog cost function they found global increasing returns to scale, but neither global economies nor diseconomies of scope in the UK higher education industry. They also found that high quality research universities are the most cost efficient in postgraduate production and the only group with increasing returns to scale in both capital and labor inputs.

The three groups of high, moderate, and low quality research universities were found to have product-specific increasing returns to scale in the production of research and undergraduate output, but only the high quality research universities had product-specific increasing returns to scale in the production of postgraduate output. Research and postgraduate output had neither economies nor diseconomies of scope for any of the groups, except in the high quality group for postgraduate output. For undergraduate output, all groups were shown to have diseconomies of scope. The often assumed cost complementarity between research and postgraduate output is not present in the UK higher education industry, while the results indicate that research and undergraduate output, and postgraduate and undergraduate output are cost anti-complements.

[43] Utilizing a flexible “fixed” cost quadratic function and using data of 158 public and 171 private US comprehensive universities for the academic year 1990–1991, Koshal and Koshal (1999) estimated global and product-specific economies of scale and scope for the US public and private higher education industries. They found evidence of ray economies of scale, global economies of scope, and a greater marginal cost of providing graduate over undergraduate education in both public and private institutions.

For private comprehensive universities, they found product-specific economies of scale in undergraduate education and research output, product-specific diseconomies of scale in graduate education, product-specific economies of scope in research, and product-specific diseconomies of scope in both undergraduate and graduate education.

For public comprehensive universities, they found product-specific economies of scale in undergraduate and graduate education, product-specific constant returns to scale in research output, and product-specific economies of scope in all output types.

[44] However, efficiency measurement studies in the higher education sector are mostly in terms of production and cost.

3.2.1. Stochastic Frontier and Data Envelopment Analyses

Research on the efficiency of colleges and universities can also be categorized by the applied empirical method, i.e., stochastic frontier analysis (SFA) or data envelopment analysis (DEA). SFA, developed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), is a nondeterministic, parametric, econometrics-based methodology that generally applies maximum likelihood techniques, which impose a functional form on the data to yield the industry frontier. Due to its simplicity and approximation of the more complex constant elasticity of substitution (CES) functional form (Stevens, 2006), the translog functional form, utilized by among others Glass, McKillop, and Hyndman (1995) in their empirical estimation of the scale and scope economies of UK universities, is most commonly used in the SFA and cost function empirical literature, while the CES (Izadi et al., 2002) and quadratic (Koshal and Koshal, 1999) functions are applied to a lesser degree. DEA, pioneered by Charnes, Cooper, and Rhodes (1978) is a deterministic, nonparametric, mathematical programming approach to relative inefficiency calculation, wherein the convexity assumption enables interpolation among observed universities in the sample to search for a best practice composite university (Glass et al., 2009).

The main feature of the SFA methodology is the estimation of a function, e.g., production or cost, with a composed error term that consists of a normally distributed random error and an inefficiency component that has a one-sided distribution. The one-sided inefficiency component is generally assumed to fit either the half-normal or exponential distributions, or the more complex yet more flexible two-parameter truncated-normal and gamma distributions that depend on both placement and spread parameters (Kumbhakar and Lovell, 2000).[45] Although the distinction of the error term into two separable components allows for distinct predictions of inefficiency and the random error, this technique does not eliminate the confounding of a potential misspecification error in the inefficiency term arising from an inappropriately imposed functional form. The implementation of production SFA is further complicated in cases of multiple-output producers, e.g., colleges and universities, where distance functions should be appropriately applied. A

[45] Both the half-normal and exponential distributions have zero mode, while their more complex and more flexible representations, the truncated-normal and gamma distributions, respectively, allow for nonzero mode. By allowing the placement of the distribution to vary, the truncated normal and gamma distributions provide a more flexible representation of the pattern of efficiency in the data (Kumbhakar and Lovell, 2000).

practical solution to the multiple-output aggregation problem in addition to the assignment of appropriate output weights is the estimation of a cost frontier that uses commonly available data on institutional costs as the dependent variable.

Besides providing a set of peers that an inefficient unit can emulate to achieve efficient operations, DEA more importantly does not burden the researcher to presume a specific functional relationship between inputs and outputs through the application of a deterministic, piecewise linear programming approach. DEA defines a frontier that 'envelopes' the observations through the maximization of a productivity ratio of weighted outputs to weighted inputs, wherein the endogenously determined weights vary per observation and calculate the best possible relative efficiency score for each institution.

In contrast to SFA, however, the deterministic methodology of DEA implies that the random error is confounded with the estimated inefficiency score, while its nonparametric approach implies that statistical tests for inputs and outputs included in the specifications and predicted relative efficiency scores are not calculated. As noted by Robst (2001), this confounding problem could become more severe in cases of large, nonhomogeneous samples of observations. To alleviate the problem, Johnes (2006) applied the Pastor, Ruiz, and Sirvent (2002) technique when comparing nested DEA models and reduced the number of inputs and outputs to be incorporated in DEA modeling to a significant set. Similarly, Johnes (2006) and Glass et al. (2009) used bootstrapping techniques in defining confidence intervals for estimated relative efficiency scores.[46]

DEA methodologies can take one of two orientations: the input-oriented DEA, which minimizes the use of resources in achieving a fixed output level; or the output-oriented DEA, which maximizes the level of output that can be achieved using a fixed level of inputs. The choice of orientation, however, only has a minimal impact on the estimated frontier and relative efficiency scores, and both orientations identify the same set of efficient and inefficient units. For the higher education sector, Joumady and Ris (2005) and Johnes (2006) recommended the output orientation given the fixed amount of inputs, e.g., the quality of entering students and the state financial resources received by colleges and universities. Meanwhile, McMillan and Chan (2006) adopted

[46] Johnes (2006) applied the Simar and Wilson (1998, 2004, 2007) procedure and Glass et al. (2009) utilized the Atkinson and Wilson (1995) methodology.

an input orientation and argued that colleges and universities have less control on outputs in the longer term. Using the DEA methodology also requires a scale assumption, i.e., constant or variable returns to scale. Joumady and Ris (2005) pointed out that the constant returns to scale assumption is appropriate in cases of an insignificant relationship between scale of operation and efficiency, otherwise variable returns to scale can be assumed.

3.2.2. Cost, Output, Input, and Input Price Indicators

For the higher education sector, stochastic production and cost frontiers are estimated more commonly than revenue and profit frontiers. The estimation of cost and production frontiers require the collection and use of slightly different data[47]: in the production version, output is the dependent variable and a set of inputs are the explanatory variables; while in the cost version, cost is the dependent variable and outputs and input prices are the explanatory variables. Research on cost SFA and cost function uses several cost indicators: variable, current, or total education and general expenditures (de Groot et al., 1991; Koshal and Koshal, 1999; Robst, 2001; McMillan and Chan, 2006), total cost (Glass et al., 1995; Izadi et al. 2002; Stevens, 2006), and average total cost (Koshal and Koshal, 1995). Although cost frontiers are more practical to estimate in the case of multiple-output production units, the unavailability of input prices for higher education institutions makes the application of DEA methodology (Johnes, 2006) more appealing since it only requires input and output data.

Instruction and research are the primary outputs of colleges and universities. Since actual instruction and research outputs, i.e., value-added knowledge obtained by students while in college and the increased knowledge base created by university research, are difficult, if not impossible, to quantify, researchers instead use intermediate outputs as proxies. Instruction output is quantified using either the number of students (total full-time and part-time students, full-time equivalent (FTE) students, or credit hours) or the number of degrees awarded, while research output valuation is in terms of research spending or revenue, or more ideally the number of publications.

[47] Among the control variables used in the higher education efficiency and cost function literature are: the control of the institution (private versus public), the presence of a medical school, state regulation, the classification of the institution (Carnegie classification), and whether the institution grants a PhD degree, among others.

Using a sample of 147 doctorate-granting US universities, de Groot et al. (1991) found that using either the number of students or degrees awarded to measure teaching output had minimal impact on their translog variable cost function estimates. Several studies of UK universities, further classify undergraduate student enrollment into arts and science majors (Izadi et al., 2002; Stevens, 2006) to acknowledge the cost structure differentials among fields of study. McMillan and Chan (2006) classified Canadian university undergraduate students into arts and science majors as well as postgraduate students into master's and doctoral-level students, the only research thus far to have made this distinction. De Groot et al. (1991) examined two indicators of research output, the arguably quality-adjusted number of publications and the amount of research spending, generally considered to be the more inferior indicator, and found that their results changed significantly depending on their choice of proxy. For UK universities, Glass et al. (1995) used the quality-sensitive UK Research Assessment Exercise (RAE) five-point scale research score to gauge research output.

Although ideal indicators of primary outputs should be quality adjusted to enable the distinction of the impact of quality and quantity on costs, this practice is not common in studies relating to American colleges and universities because reliable quality data are not accessible. In estimating cost functions for US colleges and universities, Koshal and Koshal (1995, 1999)[48] adjusted for institutional quality using the Scholastic Aptitude Test (SAT) and American College Testing (ACT) scores of incoming college freshmen and an academic reputation indicator published by the US News and World Report, while de Groot et al. (1991) used data collected by Jones et al. (1982) on peer-rated graduate program quality. The availability of quality measurements through the Research Assessment Exercises[49] and Teaching Quality Assessments make quality adjustment more accessible in the case of UK universities, although Izadi et al. (2002) argue that research grants and contracts obtained by institutions are a sufficient research quality indicator as they are reflective of both the market value of an institution's research output as well as its current research performance. In studies relating to the UK higher education sector, a few

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[48] They argued that SAT and ACT scores signal the quality of institutions, which parents and students are willing to pay more for in order to receive a higher educational quality experience.
[49] See Glass et al. (1995) for a description of the 1985/86 and 1989 Research Assessment Exercises.

researchers have also controlled for teaching output quality using the proportion of first-class and upper-second-class degrees awarded by institutions.

Among input prices, the price of labor is often incorporated into SFA research using either the overall or labor category (i.e., academic versus nonacademic) average salaries as indicators. Meanwhile, the price of capital has often been ignored mainly due to measurement difficulties and differences in accounting practices among colleges and universities. The general practice of ignoring capital input prices could, however, potentially pose an econometric problem. The cost function estimations of de Groot et al. (1991) revealed the estimated coefficients for the book value of capital to be statistically significant. While, in their analysis of scale and scope economies in UK universities, Glass et al. (1995) used capital expenses as a proportion of net assets as a proxy for capital price.

The higher education inputs generally included in the DEA efficiency literature are: the number of academic (teaching and research) and nonacademic staff; the value of non-labor spending[50]; the number of total, undergraduate, and postgraduate students; non labor-related operating expenses; and capital spending. The average A-level or Highers qualification[51] test scores of enrolled students are also used to control for teaching quality in several UK studies.

3.2.3. Efficiency Scores

There is an unclear pattern to the institutional efficiencies that can distinguish the predictions obtained from the DEA and SFA methodologies. McMillan and Chan (2006) reported a marginally higher DEA efficiency mean score of 0.95 for Canadian universities, compared to a mean SFA cost efficiency score of 0.92. For the UK, the following are predicted mean efficiencies utilizing the SFA approach: 0.79 for English and Welsh universities (Stevens, 2006), 0.85 for nonspecialist[52] UK universities (Glass et al. 2009)[53], and 0.88 for UK universities (Izadi et al. 2002); and DEA methodology: 0.93–0.95 for English universities (Johnes, 2006) and 0.79 for

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[50] For instance, on administration, library and computer facilities, interest payments, and depreciation (Johnes, 1996); energy, nonsalary payments, administration services, buildings and grounds, libraries, and student services (Katharki and Katharkis, 2010).

[51] These are the equivalents of SAT and ACT testing in the UK education system.

[52] Nonspecialist universities are those that do not highly specialize in teaching or research.

[53] The stochastic cost frontier estimations of Glass et al. (2009) do not incorporate input prices.

nonspecialist UK universities (Glass et al. 2009). Katharki and Katharkis (2010) found a mean relative efficiency score of 0.82 using DEA for a sample of Greek universities, while Robst (2001) utilized the cost SFA methodology for American colleges and universities, but did not report predicted cost efficiencies.

3.2.4. Predicting Inefficiency in SFA and DEA Methodologies

The natural extension to cost frontier research is an analysis of the drivers of efficiency. These determinants, commonly termed in the literature as environmental or nondiscretionary variables, consist of factors institutions take as given, but that influence the skillful manner, rather than the production process itself, in which colleges and universities use as few inputs as necessary to deliver instruction and research outputs. SFA and DEA methodologies also differ in their treatment of efficiency determinants in the analysis. In DEA, the estimated impact of environmental variables on inefficiency is evaluated by comparing restricted and unrestricted models. McMillan and Chan (2006) stress the importance of taking account of environmental variables in DEA to appropriately assess institutions that face relatively harsher environments.

In SFA methodology, an efficiency function that relates efficiency to environmental variables is specified. This efficiency function can be estimated using the one-step or two-step methodology. The more archaic two-step methodology separately estimates the stochastic frontier in a first stage that yields predicted efficiencies which are then used as the dependent variables in a second stage ordinary least squares (OLS) or Tobit regression analysis to investigate the efficiency determinants. Clearly, this technique violates the assumption of identical distribution on the inefficiency effects imposed in the first stage (Robst, 2001). The one-step methodology alleviates this problem by simultaneously estimating the cost frontier and the efficiency function, consequently avoiding the necessity to assume identically distributed inefficiency effects. Wang and Schmidt (2002) compared the estimators from these two SFA methodologies using Monte Carlo evidence and found that one-step methodologies yield consistent and asymptotically efficient estimators, while the two-step methodologies yield biased estimators and underdispersed predicted efficiencies.[54] Among the widely used one-step methodology panel data variants in the

[54] Appendix B provides evidence for some of the findings of Wang and Schmidt (2002) using data from this study.

literature are: time-invariant effects (Battese and Coelli, 1988); time-varying effects that assume the inefficiency effects to be an exponential function of time (Battese and Coelli, 1992; Kumbhakar, 1990); and flexible inefficiency effects characterization, which models inefficiency as a function of environmental or nondiscretionary variables (Kumbhakar, Ghosh, and McGukin, 1991; Battese and Coelli, 1995).

3.2.5. Inefficiency Determinants

In a cost frontier analysis of American public colleges and universities, Robst (2001) did not find a direct link between the share of state appropriations and tuition to total revenue on cost inefficiency. He instead found that changes over time in the share of state appropriations affect inefficiency changes. More specifically, he showed that public institutions experiencing relatively smaller declines in the revenue share of state appropriations could have greater improvements in efficiency.

For English and Welsh universities, Stevens (2006) presumed that efficiency is a function of student and staff characteristics, e.g., gender, age, race, and socioeconomic makeup, wherein the following were found to positively influence efficiency: the percentage of senior faculty, nonwhite staff, active research staff, mature students, and students from a lower social class; and the following had the opposite effect: percentage of staff over 50 years old, students achieving first class and upper-second class degrees, and female students. McMillan and Chan (2006) considered the following environmental factors for Canadian universities: success of arts and sciences faculties in securing funding from Canada's national granting councils; percentage of faculty in medical, natural, and engineering sciences; total student enrollment in universities within a 200-kilometer distance; FTE undergraduate enrollment per undergraduate degree awarded; proportion of part-time student enrollment; class size; an index of specialization among programs; total enrollment growth rate; total revenue growth rate; and total FTE enrollment.

3.2.6. Other Research on Higher Education Efficiency

Although a majority of higher education efficiency studies focuses on production and cost efficiency, there is another strand of less traditional research that uses alternative efficiency concepts, e.g., profit, financial ratios, and competencies generated during the educational process.[55] Two studies of this nature employ DEA methodology. Glass et al. (2009) used profit function concepts and financial ratios[56] to estimate relative efficiency scores and identify efficiency differentials between relatively more specialist and nonspecialist UK institutions. They found that the more specialized institutions were relatively more efficient, both in teaching and research.[57]

In a cross-country analysis of European higher education institutions Joumady and Ris (2005) used postal survey data to quantify efficiency through subjective concepts of competencies, e.g., those acquired by students upon graduation and the match of competencies gained to labor market requirements. They identified that higher education institutions in the UK, Netherlands, and Austria are most efficient, those in France and Germany are moderately efficient, and that schools in Finland, Spain, and Italy are least efficient. Their results also revealed that the most prestigious colleges are not necessarily the most efficient.

3.3. Data and Empirical Methodology

3.3.1. Data

The data in this study were primarily obtained from the Integrated Postsecondary Education Data System (IPEDS), a database of interrelated surveys conducted and maintained by the US Department of Education's National Center for Education Statistics (NCES) on colleges, universities, and technical and vocational institutions that participate in the federal student financial aid programs.[58] The IPEDS is a rich source of institutional-level data relating to institutional characteristics, admissions and test scores, tuition and pricing, enrollment, completions, graduation rates, student financial aid, finance, and human resources.

The cost frontier estimations in this research use the following information from IPEDS: total costs, outputs (enrollment and research), input prices (instruction and noninstruction labor,

[55] The estimation of profit efficiency requires data on quantities and prices of both outputs and inputs.
[56] In the financial ratios-based DEA, indicators used in the analysis represent important dimensions of corporate performance, such as: cash position, liquidity, working capital position, leverage, profitability, and turnover. The ratios included in financial ratios-based empirical analysis to represent these dimensions of corporate performance, respectively, are: cash/total assets, current assets/current liabilities, working capital/total assets, long-term liabilities/total assets, net income/total assets, and sales/total assets.
[57] Glass et al. verified their findings using a cost SFA that ignored input prices.
[58] See IPEDS website: http://nces.ed.gov.

and capital), institutional quality (Scholastic Aptitude Test (SAT)[59] math component and American College Testing (ACT)[60] Program composite 75th percentile scores of first-time, degree/certificate-seeking undergraduate students), environmental variables (student and staff characteristics as well as instruction and research cost shares), and control variables (categorical variables identifying the Carnegie Foundation classification of the schools, existence of a medical school or hospital, and institutional control). To test the sensitivity of the main results, I also used alternative quality indicators, e.g., Barron's College Admissions Selector from Profiles of American Colleges 2013, the 2014 Forbes Top Colleges rankings, and the 2015 US News and World Report Best Colleges rankings.

In this paper, analysis is limited to 2006–2011 data on four-year public and private not-for-profit American colleges and universities, primarily granting baccalaureate degrees or above, that also have 2000 Carnegie classifications as Doctoral/Research Universities (Extensive and Intensive)[61] or Master's Colleges and Universities (I and II).[62] Private-for-profit institutions were excluded from the analysis because of the unavailability of input price data for these colleges and the likelihood of them employing a different production technology. A list of the variables used in the empirical estimations and their respective summary statistics are presented in Table 24.

<Table 24> about here

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[59] According to the IPEDS website, "an examination administered by the Educational Testing Service and used to predict the facility with which an individual will progress in learning college-level academic subjects".

[60] According to the IPEDS website, "[t]he ACT assessment program measures educational development and readiness to pursue college-level coursework in English, mathematics, natural science, and social studies. Student performance does not reflect innate ability and is influenced by a student's educational preparedness".

[61] Based on the IPEDS website, "Doctoral/Research Universities-Extensive and Intensive institutions typically offer a wide range of baccalaureate programs, and are committed to graduate education through the doctorate degree. Extensive institutions award 50 or more doctoral degrees per year across at least 15 disciplines. Intensive institutions award at least 10 doctoral degrees per year across 3 or more disciplines, or at least 20 doctoral degrees per year overall."

[62] Based on the IPEDS website, "Master's Colleges and Universities I and II institutions typically offer a wide range of baccalaureate programs and are committed to graduate education through the master's degree. Master's I institutions award 40 or more master's degrees per year across 3 or more disciplines, while Master's II institutions award 20 or more master's degrees per year."

3.3.2. Empirical Methodology

Stochastic production frontier analysis was pioneered independently by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). Production analysis concepts can be similarly applied in the estimation of the technology parameters of a cost frontier and consequently the prediction of cost inefficiencies. Kumbhakar and Lovell (2000)[63] as well as Coelli et al. (2005) provide in-depth theoretical and empirical analyses of stochastic production and cost frontier models, which provide the foundations of the empirical methodology discussion that follows.

Suppose that higher education institutions have expenditure that can either be equal to or greater than the industry's cost frontier so that:

$$E_{it} \geq c(y_{it}, w_{it}, Z_{it};\ \propto, \beta) \tag{1}$$

where E_{it} is total, actual, and observed expenditure of institution $i=1,\ldots,I$ at time $t=1,\ldots,T$; $c(.)$ is the deterministic cost frontier common to all producers; y_{it} is a vector of outputs; w_{it} is a vector of input prices; Z_{it} is a vector of institution-specific variables that also affect an institution's level of expenditure; and α and β are vectors of technology parameters to be estimated. The total expenditure, E_{it}, is the sum of $w_{it}x_{it}$, where x_{it} is a vector of inputs not necessarily observed. For instance, total expenditure data are readily available for higher education institutions but the actual quantity of inputs used (e.g., the number of computer hours utilized, proportion of books in the library that contributed to learning during a given semester, actual depreciation value of classroom equipment) and corresponding prices are difficult, if not impossible, to disentangle. Since input quantity or input cost share data are required in the decomposition of total cost inefficiency into input-oriented technical and input allocative inefficiencies but are not available for the higher education sector, I only predict total cost inefficiency.

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[63] Kumbhakar and Lovell (2000) also chronicle the differences between stochastic production and cost frontier analyses. Differences between the estimation of stochastic production and cost frontiers are due to the following: (1) Data requirements: estimation of a stochastic production frontier (SPF) requires input and output data, while estimation of a stochastic cost frontier (SCF) requires expenditure, output, and input price data. (2) Multiple outputs: a simple SPF model only allows for a single-output producer unless a distance function is estimated, while the SCF easily allows for the inclusion of multiple outputs. (3) Variable versus quasi-fixed inputs: SCF estimation allows for the classification of inputs into variable and quasi-fixed types via the estimation of a variable cost frontier, while the SPF estimation does not. (4) Behavioral assumptions: SPF estimations assume output maximization while SCF estimations assume cost minimization. (5) Efficiency measure: cost efficiency can be further partitioned into input-oriented technical efficiency and input allocative efficiency given availability of input cost share or input quantity data, while output-oriented technical efficiency obtained from estimation of a SPF cannot be decomposed further.

Given that a deterministic cost frontier assumes that the observed expenditure of colleges and universities cannot exceed a minimum feasible cost for reasons other than cost inefficiency (e.g., extreme weather, luck, data measurement error), a stochastic cost frontier model is intuitively more appropriate. A stochastic cost frontier can be written as:

$$E_{it} \geq c(y_{it}, w_{it}, Z_{it};\ \propto, \beta) \cdot exp\{v_{it}\} \tag{2}$$

where the stochastic component is the producer-specific random element $exp\{v_{it}\}$.

Utilizing a log-linear Cobb-Douglas functional form, the general stochastic cost frontier model in equation (2) can be written in the following specific form:

$$lnE_{it} \geq \propto_o + \sum_{j=1}^{J} \propto_j \ ln\, y_{jit} + \sum_{k=1}^{K} \beta_k \, ln\, w_{kit} + \sum_{m=1}^{M} \emptyset_m Z_{mit} \ + v_{it} \tag{3}$$

Incorporating the nonnegative cost inefficiency term u_{it} transforms equation (3) into:

$$lnE_{it} = \propto_o + \sum_{j=1}^{J} \propto_j \ ln\, y_{jit} + \sum_{k=1}^{K} \beta_k \, ln\, w_{kit} + \sum_{m=1}^{M} \emptyset_m Z_{mit} \ + v_{it} + u_{it} \tag{4}$$

where $\varepsilon_{it} = v_{it} + u_{it}$ is the composed error term and the cost inefficiency component u_{it} is assumed further as a function of several environmental factors.

This paper builds on the higher education efficiency literature in assuming that the inefficiency effects are functions of the student body and staff characteristics, as well as the shares of instruction- and research-related expenditure to total spending. This is represented by the following equation that is simultaneously estimated with the stochastic cost frontier in equation (4):

$$u_{it} = W_{it}\tau + \varphi_{it} \tag{5}$$

where u_{it} is the nonnegative cost inefficiency, W_{it} is a vector of environmental variables that impacts the cost inefficiency of institution *i* and varies with time *t*, and τ is a vector of parameters to be estimated. The Battese and Coelli (1995) variant of the one-step estimation of the cost frontier and the inefficiency effects equation is applied in this case.

The following categories of environmental factors are considered in the inefficiency effects equation (5): (1) student characteristics: percentage of students who are part-time, undergraduates aged 25 and over, nonwhite, female, and science majors; (2) staff characteristics: percentage of female instructors, professors to total teaching positions, and nonwhite staff; and (3) cost shares: instruction and research cost shares, as well as the corresponding squared terms. The squared terms of instruction- and research-related spending were incorporated in the specifications to capture plausible nonlinearities in the relationship between cost shares and cost inefficiency effects. Unlike in the two-step frontier specifications, the inefficiency effects distribution varies with W_{it} in the one-step specification and therefore is no longer assumed to be identically distributed. More specifically, the following assumptions apply on the error components:

(a) v_{it} is the idiosyncratic error term that is independently and identically distributed (iid) with normal distribution [iid $N(0, \sigma_v^2)$];

(b) u_{it} is the non-negative, time-variant inefficiency term that is independently distributed as truncations at zero of the $N^+(W_{it}\tau, \sigma_u^2)$ distribution; and

(c) φ_{it} is a random variable defined by the truncation of the normal distribution with zero mean and variance σ^2, such that the point of truncation is $-W_{it}\tau$ or $\varphi_{it} \geq -W_{it}\tau$.

To satisfy the cost function linear input price homogeneity condition, I impose the following constraint on the Cobb-Douglas cost frontier equation (4):

$$\sum_{k=1}^{K} \beta_k = 1. \tag{6}$$

Incorporating the input price homogeneity condition equation (6) into equation (4) yields the following Cobb-Douglas stochastic frontier appropriate for empirical estimation:

$$lnE_{it} - lnw_{1it} = \propto_o + \sum_{j=1}^{J} \propto_j \; ln\, y_{jit} + \sum_{k=2}^{K} \beta_k \,(ln\, w_{kit} - lnw_{1it}) + \sum_{m=1}^{M} \emptyset_m z_{mit} + v_{it} + u_{it} \tag{7}$$

Although the Cobb-Douglas functional form has a simple structure that allows emphasis on cost efficiency predictions and a dual property that permits transformation between production and cost frontiers, a misspecification error will lead to biased predicted inefficiencies if the production technology turns out to be more complex. Hence for this reason I also explore the translog and quadratic stochastic cost frontier functions.

The translog cost frontier introduced by Christensen, Jorgenson, and Lau (1971) has the following appealing properties: it easily handles multiple output cases, has flexibility via a second-order approximation to any well-behaved underlying cost frontier at the mean of the data, and yields unbiased cost frontier and cost inefficiency estimators. Given these features, I utilize the translog functional form as the preferred specification to estimate the stochastic cost frontier, predict the cost inefficiencies, and determine the environmental factors that affect an institution's cost inefficiency. However, since the translog functional form has no known dual property and multicollinearity among the regressors is likely to lead to imprecise estimated parameters, including those related to the composed error term, estimations of the Cobb-Douglas and quadratic functional forms remain insightful and potentially useful. Assuming multiple output and input prices, the translog cost functional form of the stochastic frontier takes the following form:

$$
\begin{aligned}
lnE_{it} = & \propto_0 + \sum_{j=1}^{J} \propto_j \ ln\, y_{jit} \\
& + \sum_{k=1}^{K} \beta_k\, ln\, w_{kit} \\
& + \frac{1}{2}\sum_{j=1}^{J}\sum_{n=1}^{N} \sigma_{jn}\, ln\, y_{jit} lny_{nit} \\
& + \frac{1}{2}\sum_{k=1}^{K}\sum_{q=1}^{Q} \gamma_{kq}\, ln\, w_{kit} lnw_{qit} + \sum_{j=1}^{J}\sum_{k=1}^{K} \delta_{jk} ln\, y_{jit} ln\, w_{kit} + \sum_{m=1}^{M} \emptyset_m Z_{mit} + v_{it} \\
& + u_{it}
\end{aligned}
\tag{8}
$$

The price homogeneity condition for the translog functional form requires the following set of restrictions (Zardkoohi, Rangan, and Kolari, 1986):

$$\textstyle\sum_{k=1}^{K} \beta_k = 1, \tag{9}$$

$$\textstyle\sum_{k=1}^{K} \gamma_{kq} = 0, \text{ and} \tag{10}$$

$$\textstyle\sum_{k=1}^{K} \delta_{jk} = 0. \tag{11}$$

Imposing constraints (9)–(11) on the translog stochastic cost frontier equation (8) results in the following homogeneity-constrained empirical cost frontier suitable for estimation:

$$
\begin{aligned}
lnc_{it} - lnw_{it} = & \alpha_o \\
& + \sum_{j=1}^{J} \propto_j y_{jit} + \sum_{k=2}^{K} \beta_k (lnw_{kit} - lnw_{1it}) + \frac{1}{2}\sum_{j=1}^{J}\sum_{n=1}^{N} \sigma_{jn} lny_{jit} lny_{nit} \\
& + \frac{1}{2}\sum_{k=1}^{K-1}\sum_{q=k+1}^{K} \gamma_{kq} f_{kqit} + \sum_{j=1}^{J}\sum_{k=k1}^{K} \delta_{jk} g_{jkit} + \sum_{m=1}^{M} \emptyset_m Z_{mit} + u_{it} \\
& + v_{it}
\end{aligned}
\tag{12}
$$

where

$$f_{kqit} = (lnw_{kit}lnw_{qit}) - 0.5(lnw_{kit})^2 - 0.5(lnw_{qit})^2 \quad (13)$$

$$g_{jkit} = lny_{jit}(lnw_{k1it} - lnw_{k2it}). \quad (14)$$

In the empirical implementation of equations (12)–(14), college and university outputs considered are (1) instruction: FTE undergraduate and graduate student enrollment; and (2) research, proxied by total revenue from federal and state grants and contracts. The input prices incorporated in the analysis are: (1) instructional labor price: average salary outlays and fringe benefit expenses allocated to instruction, research, and public service-related staff; (2) noninstructional labor price: average salary outlays and fringe benefit expenses for all other expense categories, e.g., academic support, student services, institutional support, operation and maintenance of plant, independent operations, and auxiliary enterprises, among others; and (3) capital price: capital depreciation expense per FTE staff. The price homogeneity condition is imposed using capital price as the normalizing price variable and an empirical specification using the total number of students as the instruction output is also considered.

The Barron's College Admissions Selector is the main institutional quality proxy used in the empirical estimations. The selector is represented by categorical variables that classify higher education institutions into the five Barron's groupings, i.e., most competitive, very competitive, highly competitive, competitive, and less competitive/noncompetitive, wherein the base group is the less competitive/noncompetitive category. Four alternative institutional quality indicators were also explored to confirm the relevance and effect of adjusting for institutional quality in cost function and frontier analyses. These are the annual SAT math and ACT[64] program composite 75th percentile scores of admitted first-time, degree/certificate-seeking undergraduate students, the 2014 Forbes Top Colleges rankings, and the 2015 US News and World Report Best Colleges rankings. Although it is often argued that institutional quality is ideally represented by a combination of, among others, the quality of classroom instruction, average student ability, and sufficiency of school facilities, these factors are difficult to quantify. But since school administrators admit students that match the institution's corresponding level of quality, while students base their school choices on their own assessment of their personal academic abilities

[64] Koshal and Koshal (1995) use SAT score to represent quality in their estimation of higher education cost functions and utilized the Harford and Marcus (1986) methodology to convert ACT scores to SAT scores for missing SAT data.

(Light, 2000), these proxies should provide suitable representations of both student and institutional quality.

Control categorical indicators to account for differential cost structures between public and private institutions, colleges and universities with medical schools and hospitals, and Carnegie categories (DRUE, DRUI, and MCU-I; base: MCU-II) were also included in the empirical specifications. All dollar values were deflated using the chain-weighted Consumer Price Index-All Urban Consumers (1982–1984=100) published by the US Department of Labor's Bureau of Labor Statistics.

The Frontier Version 4.1c program, specifically written to estimate the model specifications detailed in Battese and Coelli (1988, 1992, and 1995) and Battese, Coelli, and Colby (1989), was used to estimate the maximum likelihood estimation (MLE) parameters of the stochastic cost frontier (equations (4) and (12)) and inefficiency effects equation (5). This program utilizes the Davidon–Fletcher–Powell (DFP) quasi-Newton method and the Battese and Corra (1977) parameterizations to obtain the maximum likelihood estimates.[65] The Battese and Corra method utilize $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/(\sigma_v^2 + \sigma_u^2)$ to calculate the maximum likelihood estimates, in which the parameter γ that lies between 0 and 1 provide the starting value for the iterative maximization process of the DFP algorithm.

The next step is the prediction of the school-level cost inefficiencies, u_{it}, through the Jondrow et al. (1982) procedure of extracting information on u_{it} contained in the composed error term ε_{it} using the conditional distribution $f(u|e)$. Once the predicted values of u_{it} are obtained, the cost inefficiencies can be predicted using the Battese and Coelli (1988) point estimator[66]:

$$CE_{it} = E(\exp\{u_{it}\}|\varepsilon_{it}) \tag{15}$$

such that the predicted cost inefficiencies that range from 1, for the cost-efficient institutions, to infinity measure the distance of a school's observed costs from the estimated cost frontier. The stochastic production frontier likelihood function, the corresponding partial derivatives, and prediction of the technical efficiencies are presented in Battese and Coelli (1993), from which a

[65] For more information on the Frontier Version 4.1 program, see Coelli (1996).

[66] A less preferred alternative is the Jondrow et al. (1982) estimator $CE_{it} = \exp\{u_{it}\}$, which is only a first-order approximation to the Battese and Coelli estimator (Kumbhakar and Lovell, 2000).

few sign changes transform the likelihood function and parameter estimators into the cost counterparts (Coelli, 1996).

In addition to the estimation of the Battese and Coelli (1995) specification, estimates were also obtained for the time-variant Battese and Coelli (1992) parameterization of time effects, which assumes that the inefficiency term is a truncated normal random variable multiplied by a specific function of time:

$$u_{it} = exp\{-\rho(t - T_i)\}u_i \quad (16)$$

where t is the current time period, T_i is the final time period observed that also represents the base level of inefficiency, and ρ is the decay parameter indicating whether the level of inefficiency is increasing (ρ<0), decreasing (ρ>0), or constant (ρ=0) over time. If ρ=0, the time-varying decay model collapses to the time-invariant model. The 1992 and 1995 Battese and Coelli stochastic frontier models are, however, non-nested and therefore cannot be compared using likelihood ratio tests[67] (Coelli, 1996).

The following assumptions on the error components u_{it} and v_{it} are adopted in the Battese and Coelli (1992) model:

(a) v_{it} is the idiosyncratic error term that is independently and identically distributed (*iid*) with normal distribution [iid $N(0, \sigma_v^2)$];

(b) u_{it} is the inefficiency term that is independently and identically distributed (*iid)* with a truncated normal [iid $N^+(\mu, \sigma_u^2)$] distribution; and

(c) v_{it} and u_{it} are distributed independently of each other, and of the regressors.

3.4. Results

3.4.1. Preliminary Specifications

Tables 25 and 26 present the stochastic cost frontier and inefficiency effects equations, respectively, from both the preliminary and preferred specification. Each column in both tables represents a different specification for the inefficiency effects equation as the cost frontier specification remains the same. The following environmental variables were presumed as cost inefficiency determinants: exponential function of time (column 1); instruction and/or research

[67] For a more detailed description of the statistical tests used in this paper, e.g., Hausman and likelihood ratio tests, see Wooldridge (2013).

cost shares and their quadratic terms (columns 2–4); student characteristics (column 5); staff characteristics (column 6); and a combination of two or more categories of environmental factors (columns 7–10).

The preferred specification in column 10 presumes the following as inefficiency determinants: spending share of instruction and research including their quadratic terms, percentage of part-time students and undergraduate students aged 25 and over for the student characteristics, and percentage of female instructors, professors, and nonwhite staff for the staff characteristics. The decision to drop some student characteristics from the main specification was based on the high correlation of the race and gender student characteristics with their staff counterparts (nonwhite staff and students: 0.66; female staff and students: 0.78), and the proportion of science students turned out as statistically insignificant in the preliminary estimations.

The following general results, consistent across specifications, were obtained relating to the cost frontier: (1) the estimated coefficients for outputs and input prices, and their interaction terms, are statistically significant; (2) colleges and universities that own hospitals or grant medical degrees have higher costs; (3) DRUE, DRUI, and MCU-I (relative to the base group MCU-II institutions) generally have statistically significant positive estimated coefficients of decreasing magnitude; and (4) public institutions are estimated to operate at a lower cost structure compared to private not-for-profit institutions. The last result is in contrast with de Groot et al.'s (1991) finding of invariant cost structure between public and private doctorate-granting American universities.

The estimated coefficients for the Barron's quality proxies are statistically significant in most specifications that incorporate two or more categories of inefficiency effects explanatory variables (columns 7–10). In Columns 8 and 10, the dummy variables for the most competitive, very competitive, and highly competitive colleges and universities have positive, statistically significant estimated coefficients of decreasing magnitude, implying that higher spending is necessary to deliver a better quality of education.

For the inefficiency effects, instruction and research cost shares and student and staff characteristics are found to impact cost inefficiency. In particular, the estimated linear and quadratic coefficients of instruction cost share imply that schools approach the cost frontier as the share of instruction spending rises. Although the estimated coefficients for the linear and quadratic instruction cost shares are respectively positive and negative statistically significant, the relatively low predicted pivot points for instruction cost shares of 14.9 (column 4) and 6.06 percent (column 10) are of little practical significance given that most observations in the data are on the downward-sloping section of the instruction share distribution. In columns 2 and 8, only instruction cost share terms with negative estimated coefficients are statistically significant.

There is also a clear pattern that emerges with regard to the impact of research spending on cost inefficiency. The results show that the estimated coefficients for the linear and quadratic terms of the research cost share are respectively positive and negative, and statistically significant in all relevant specifications (columns 3, 4, 9, and 10). The turning points are estimated within the research cost share range of 44–87 percent, beyond which all observations would only be the highly research-intensive institutions.

When only student characteristics are considered to impact inefficiency effects, none of the five characteristics are statistically significant (column 5), but this changes as other categories are incorporated in the analysis. The estimated coefficients are statistically significant but of unstable signs for the percentage of part-time students (columns 7–10) and consistently positive and statistically significant for the percentage of undergraduate students aged 25 and over (columns 8–10). In the preferred specification (column 10), these two student characteristics have positive and statistically significant estimated coefficients. The results for staff characteristics are more consistent across relevant specifications. The estimated coefficients for the percentage of female instructors, professors, and nonwhite staff are positive and statistically significant in columns 6–10.

<Table 25 and 26 about here>

3.4.2. <u>Preferred Specification and Alternative Quality Indicators</u>

Besides the Barron's College Admissions Selector, I also use alternative quality indicators to test the stability of the estimated coefficients of the preferred specification and to predict the required cost outlay of a given rise in quality level, represented by changes in institutional grouping, the mean admission test score, or ranking. The abridged stochastic cost frontier estimation results reported in Tables 27 and the inefficiency effects estimation results in Table 28 are of specifications that use alternative quality indicators: no quality proxy (column 1), a replication of the preferred specification that used the Barron's College Admissions Selector (column 2), SAT math 75th percentile score (column 3), ACT composite 75th percentile score (column 4), 2014 Forbes Top Colleges rankings (column 5), and 2015 US News and World Report Best Colleges rankings (column 6). Since the estimated coefficients for the output and input price variables in the stochastic cost frontier are comparable across specifications of alternative quality indicators, these results are not shown. Similarly, the estimates also indicate that DRUE, DRUI, and MCU-I institutions incur higher costs of decreasing magnitude than MCU-II institutions, ownership of hospitals or medical degree-granting institutions raise costs, and public institutions operate with a lower cost structure than their private non-for-profit counterparts.

As pointed out earlier, institutions that belong to higher quality categories of the Barron's College Admissions Selector incur higher costs. In particular, colleges and universities classified as most competitive, very competitive, and highly competitive are estimated to incur 13.0, 6.9, and 4.8 percent higher costs than less competitive/noncompetitive institutions (column 2). Using the ACT and SAT test scores as quality indicator estimates shows that administrators who would like to raise their school's admission test scores by 1 percent should also be willing to raise costs by 0.23–0.25 percent (columns 3 and 4).

The two college rankings published by Forbes and US News and World Report permit the cost equivalence estimation of a desired rise in school rankings. The results provide further confirmation that delivery of high quality education comes at a cost. Based on the estimations in column 5, a rise of ten places in the Forbes rankings is estimated to raise a college's total costs by about 2.4 percent. Meanwhile, the US News and World Report methodology of ranking colleges by category yields more detailed information. The estimates show that a rise of 10 places in a college's ranking in the national universities, national liberal arts colleges, regional universities, and regional colleges categories is estimated to raise total institutional costs by about 4.5, 6.2, 7.9, and 9.6 percent, respectively. The observed increasing estimated costs of raising rankings for the smaller college groups could be explained by the lower total cost base for smaller colleges.

The results for the inefficiency effects determinants are consistent across specifications using alternative quality indicators. The estimated coefficients for student and staff characteristics are all positive and statistically significant, implying that cost inefficiency rises when any of the following proportions increase: part-time students, undergraduates aged 25 and over, female instructors, professors, and nonwhite staff. Similar to findings in the preferred specification, the estimated coefficient for instruction cost share is negative and statistically significant and there exists a quadratic relationship between research cost share and cost inefficiency. Cost inefficiency generally rises with research cost share with predicted pivot points at around 45–50 percent. The relationships between instruction and research cost shares, on the one hand, and inefficiency effects, on the other, were also found to be robust to a specification with interaction terms between the cost shares and a Carnegie Foundation classification categorical variable for DRUE and DRUI institutions.

The predicted cost inefficiencies obtained from the analysis indicate that American colleges and universities operate about 30–32 percent above the cost frontier, or equivalently at 76–77 percent cost efficiency. Both the estimated gammas for all specifications (greater than 0.90) and likelihood ratio tests of the one-sided error confirm the relative importance of the inefficiency component in the composed error term in the estimated cost frontiers for the US higher education sector.

<Tables 27 and 28 about here>

3.4.3. <u>Overestimated Public Dummy Coefficients</u>

The results from Table 27 suggest another important but often overlooked finding, that failure to control for institutional quality in cost frontier and function estimations would lead to overestimated public dummy coefficients.[68] In specifications that incorporate quality indicators (columns 2–6), public institutions are estimated to incur about 20–22 percent lower total costs than private not-for-profit institutions. The cost impact of institutional control, however, rises if the cost frontier specification ignores the quality effects. In a specification that ignores the quality indicators (column 1) public institutions are estimated to incur about 24 percent lower total costs. Hausman tests indicate that these differences in the public dummy estimated coefficients are statistically significant at the 1 percent level.

The resulting overestimated public dummy coefficients could be explained by the clear delineation between public and private institutions on the basis of quality. Since public institutions

[68] Estimated coefficients of other explanatory variables are stable across specifications that exclude and include quality variables. Moreover, the mean cost efficiency scores across the two specifications are very similar.

are of lower quality than private institutions, on average, the omitted quality bias is plausibly misattributing the impact of institutional quality on total costs onto institutional control. Among public institutions in the data, the logarithmic means of the SAT math and ACT composite 75th percentile scores of entering freshmen are respectively 5.02 and 2.63, while the corresponding values for private institutions are respectively 5.49 and 2.73. Moreover, the proportion of public institutions classified most, highly, and very competitive in the Barron's College Admissions Selector are also lower than private institutions but higher in the competitive and less competitive/noncompetitive groupings.[69] Finally, the mean Forbes and US News and World Report rankings of public institutions are also lower than those of their private counterparts.[70]

3.4.4. Hypotheses Tests

The estimates for the variance parameter, $\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$, are statistically significant and close to 1 in the preferred specifications (columns 2–6) in Table 28. This indicates that the inefficiency effects equation should be estimated with the cost frontier using the one-step methodology. Results of the generalized likelihood ratio tests of the null hypotheses that the inefficiency effects are absent or have simpler distributions are presented in Table 29. The null hypotheses tested are: (1) the variance parameter is equal to zero, implying that schools are fully efficient[71]; (2) the inefficiency effects equation has a constant term equal to zero; (3) the inefficiency effects are not a linear function of student, staff, and cost share characteristics; and (4) the traditional mean response function or OLS is the preferred estimation procedure for the cost function, meaning the inefficiency effects equation can be ignored. These four null hypotheses are rejected at the 1% level of significance justifying the use of preferred specifications that

[69] The proportions of public institutions in the sample categorized as most competitive, highly competitive, very competitive, competitive, and less competitive/noncompetitive are 1.6, 6.5, 18.9, 50.8, and 18.4 percent, respectively, while the corresponding values for private institutions are 9.1, 7.1, 23.5, 47.5, and 9.3 percent, respectively.

[70] The mean Forbes rankings are 224.3 and 135.8 for public and private institutions, respectively. The US News and World Report mean rankings for public national universities, national liberal arts colleges, regional universities, and regional colleges are 145.2, 179.8, 86.6, and 141.8, respectively, while the corresponding values for private institutions are 94.5, 159.1, 66.1, and 38.5, respectively.

[71] If the parameter γ is zero, then the variance of the inefficiency effects is zero and the model reduces to a traditional mean response function in which the inefficiency determinants of the student, staff, and cost share characteristics are explanatory variables in the cost function. In this case, the constant and time parameters are not identified. Hence, the critical value for the test statistic of the first null hypothesis is obtained from the χ_3^2-distribution.

incorporate quality indicators into the cost frontier as well as presume inefficiency effects as a function of staff, student, and cost share characteristics.

<Table 29 about here>

3.4.5. Cobb-Douglas and Quadratic Functional Forms

As a final sensitivity check of the stability of estimates, I also fitted the main specification (Tables 25 and 26, column 10) into Cobb-Douglas[72] and quadratic cost functions. The results in Table 30 show the signs of the estimated coefficients for the control explanatory variables in the cost frontier (quality indicators and public, medical, hospital, and Carnegie classification dummy variables) are the same across the three functional forms. In addition, the orders of magnitude of the estimated coefficients for quality and the Carnegie indicators using the Cobb-Douglas and quadratic functions are similar to the translog functional form estimations.

Moreover, the signs of the estimated coefficients for the environmental variables in the inefficiency effects equation in Table 31 are the same across the three functional forms only with the exception of research cost share. In the Cobb-Douglas and quadratic cost frontier estimates, the relationship between research cost share and cost inefficiency is reversed, i.e., cost inefficiency first falls and then rises as research cost share increases, with pivot points at 24.5 percent and 31.8 percent. Likelihood ratio tests that compare the three nested models, however, indicate that the translog functional form is preferable for estimating the cost frontier for the US higher education sector.

<Tables 30 and 31 about here>

3.4.6. Correlation of Predicted Cost Efficiencies

Finally, I investigate the correlation coefficients among predicted cost efficiencies across specifications and functional forms to obtain an idea of the importance of correctly specifying the cost frontier. The pairwise Pearson correlation coefficients in Table 32 reveal the following with regard to predicted cost inefficiencies: (1) low correlation (0.14–0.21) between specifications that

[72] The Cobb-Douglas frontier estimates provide evidence of the positive relationship between total cost and the outputs and input prices. The estimated coefficients for the outputs and input prices are positive and statistically significant, except for noninstructional labor price.

presume inefficiency effects to be an exponential function of time only and specifications with more explicit inefficiency effects characterization; (2) high correlation (0.98–1.00) among the preferred translog specifications that use alternative quality indicators; (3) high correlation (0.99–1.00) between a translog specification with and without the quality indicators; (4) moderately high correlation (0.68–0.90) among Cobb-Douglas, quadratic, and translog functions; and (5) a similar correlation pattern across specifications and functional forms when instruction output is proxied with the total number of students.

These correlation patterns hold as well for the Spearman rank correlation reported in Table 33, except for two notable differences: (1) moderate correlation (0.49–0.60) between exponential time and other specifications and (2) lower correlation (0.53–0.62) between the translog cost frontiers and the Cobb-Douglas and quadratic functional forms. The analysis of the correlation coefficients implies that different functional forms and inefficiency effects characterization are likely to result in moderately correlated predicted cost inefficiencies and that the omitted variable bias caused by the omission of institutional quality in cost frontier estimations manifesting in overestimated public dummy coefficients only has a negligible impact on predicted cost inefficiencies.

<Tables 32 and 33 about here>

3.5. Conclusion and Discussion

Using a translog cost function and the one-step methodology developed by Battese and Coelli (1995) the findings of this research suggests that the average American college or university operates at about 30 percent above the cost frontier of the US higher education sector. This implies that economic shocks that translate into budget cuts, particularly lower state appropriations or tuition revenue, could possibly be absorbed by colleges and universities without a decrease in output through operational efficiency improvements. To put the estimates into perspective, the 77 percent cost efficiency predicted in this paper for the US higher education sector is comparable to the 79–85 percent predictions for English and Welsh (Stevens, 2006), nonspecialist UK (Glass et al., 2009), and Greek universities (Katharki and Katharkis, 2010) but significantly lower than the 92–95 percent cost efficiency predicted for English (Johnes, 2006) and Canadian universities (McMillan and Chan, 2006).

The comprehensive analysis of alternative quality indicators also reveals that omission of institutional quality in cost frontier analyses misattributes the impact of college quality on costs onto the college's control type and manifests in overestimated public dummy coefficients. This finding could be explained by the relatively lower quality level of public colleges and universities. Furthermore, this research finds that institutions that offer a wider range of outputs, own hospitals, and operate medical schools have higher cost structures.

The research also demonstrates that inefficiency in American colleges and universities can be explained by the composition of their staff, students, and costs. In contrast, however, to English and Welsh universities (Stevens, 2006), this paper finds that the proportions of mature students, senior faculty, and nonwhite staff, as well as higher proportions of part-time students and female instruction staff, have increasing effects on the cost inefficiency of American colleges and universities.

Also, while Glass et al. (2009) found a simple, polarized result of higher efficiency among nonspecialist UK universities that are both highly instruction- and research-specialized, this is only true for instruction-intensive US higher education institutions. For research spending, this study finds that inefficiency generally increases with research cost share and eventually eases only for highly specialized research institutions, e.g., the Georgia Institute of Technology, Massachusetts Institute of Technology, New Mexico Institute of Mining and Technology, and the University of Maryland-Baltimore. The results obtained in this research suggest only partial empirical evidence of the theory of comparative advantage exists in the US higher education sector case whereby increasing specialization toward instruction results in higher cost efficiency. This could be explained by the trial and error experiments that go along with research, the inability of cost shares or research revenues to represent research quality, or the lack of suitability of the data on nonspecialist UK universities used by Glass et al. (2009).

Finally, one unresolved issue with regard to the relationship between institutional quality and efficiency deserves to be clarified. While some might argue that high-ranking institutions could deliver a better quality of education by being cost efficient, further analysis of the results in this research are supportive of the findings of Joumady and Ris (2005) relating to European higher education institutions that there is only a very weak link, if at all, between quality and efficiency, i.e., the best schools are not necessarily cost efficient.

In future research, alternative proxies for research output that are more representative of research quality, and instruction outputs could be explored, such as the number of science and nonscience students and degrees awarded. Preliminary results obtained from using alternative instruction output indicators imply the employment of unique production technologies, which in turn yield uncorrelated inefficiency levels. Also, given the poor performance of American high school students in international achievement tests in comparison to their counterparts in other industrialized countries, an inquiry into the cost efficiency of the US high school education system might also provide meaningful insights.

APPENDIX A. TABLES

Table 1. Summary Statistics (Attendance), Alternative Time Windows*

Explanatory Variables	1982–1985			1983–1986			1984–1987		
	Attend = 0 & 1	Attend = 0	Attend = 1	Attend = 0 & 1	Attend = 0	Attend = 1	Attend = 0 & 1	Attend = 0	Attend = 1
Ability	0.01	-0.04	0.38	-0.03	-0.07	0.33	-0.07	-0.09	0.25
	(0.70)	(0.69)	(0.69)	(0.70)	(0.69)	(0.68)	(0.69)	(0.69)	(0.68)
Male	0.50	0.50	0.48	0.50	0.50	0.48	0.49	0.50	0.47
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
White	0.69	0.69	0.69	0.69	0.69	0.69	0.68	0.68	0.66
	(0.46)	(0.46)	(0.46)	(0.46)	(0.46)	(0.46)	(0.47)	(0.47)	(0.47)
Never married	0.56	0.53	0.81	0.52	0.50	0.75	0.48	0.47	0.67
	(0.50)	(0.50)	(0.40)	(0.50)	(0.50)	(0.43)	(0.50)	(0.50)	(0.47)
High school GPA	1.69	1.64	2.09	1.72	1.69	1.98	1.76	1.74	1.91
	(1.20)	(1.18)	(1.30)	(1.17)	(1.15)	(1.30)	(1.13)	(1.12)	(1.28)
Father's education	10.23	10.07	11.52	10.09	9.96	11.30	9.98	9.88	11.06
	(3.68)	(3.66)	(3.57)	(3.71)	(3.70)	(3.62)	(3.72)	(3.71)	(3.69)
Mother's education	9.26	9.03	11.11	9.09	8.90	10.88	8.94	8.80	10.59
	(4.91)	(4.85)	(5.04)	(4.91)	(4.86)	(5.03)	(4.92)	(4.88)	(5.08)
Three-year per capita household	8.26	8.26	8.24	8.29	8.29	8.28	8.34	8.34	8.30
income average (in log)	(1.71)	(1.69)	(1.89)	(1.75)	(1.73)	(1.91)	(1.75)	(1.73)	(1.97)

Table 1. (Continued) Summary Statistics (Attendance), Alternative Time Windows*

Explanatory Variables	**1982–1985**			**1983–1986**			**1984–1987**		
	Attend = 0 & 1	**Attend = 0**	**Attend = 1**	**Attend = 0 & 1**	**Attend = 0**	**Attend = 1**	**Attend = 0 & 1**	**Attend = 0**	**Attend = 1**
Newspaper, magazine, or library	0.91	0.91	0.95	0.91	0.90	0.95	0.90	0.90	0.94
card in household at age 14	(0.28)	(0.29)	(0.22)	(0.29)	(0.30)	(0.22)	(0.30)	(0.30)	(0.23)
Lived with both parents at age 14	0.69	0.68	0.72	0.68	0.67	0.71	0.67	0.67	0.70
	(0.46)	(0.46)	(0.45)	(0.47)	(0.47)	(0.45)	(0.47)	(0.47)	(0.46)
Unemployment rate	8.39	8.33	8.84	8.08	7.99	8.97	7.26	7.26	7.24
	(4.82)	(4.86)	(4.46)	(4.68)	(4.64)	(4.95)	(3.85)	(3.83)	(4.12)
Age	22.47	22.66	20.90	23.13	23.29	21.57	23.99	24.11	22.55
	(2.18)	(2.13)	(1.97)	(2.35)	(2.30)	(2.29)	(2.51)	(2.46)	(2.57)
Number of observations	21106	18803	2303	21250	19269	1981	20518	18861	1657

GPA = grade point average.

*Note: Values in parentheses are standard errors.

Table 2. Summary Statistics (Completion), 1984–1987 Time Window*

Explanatory Variables	Completion = 0 & 1	Completion = 0	Completion = 1
Faculty-student ratio	0.01	0.01	0.02
	(0.03)	(0.02)	(0.03)
Instruction spending (in log)	1.08	0.80	1.32
	(1.51)	(1.36)	(1.60)
Research spending (in log)	0.20	0.12	0.27
	(1.14)	(0.93)	(1.29)
Academic-related spending (in log)	1.19	0.88	1.46
	(1.68)	(1.50)	(1.78)
Financial aid spending (in log)	0.50	0.31	0.67
	(0.85)	(0.68)	(0.94)
Total spending (in log)	1.46	1.08	1.79
	(2.04)	(1.82)	(2.16)
Public institution	0.20	0.26	0.15
	(0.40)	(0.44)	(0.36)
Two-year institution	0.02	0.04	0.01
	(0.16)	(0.19)	(0.12)
Northeast	0.20	0.15	0.24
	(0.40)	(0.36)	(0.43)
North Central	0.22	0.20	0.24
	(0.42)	(0.40)	(0.43)
West	0.16	0.18	0.15
	(0.37)	(0.38)	(0.35)
South	0.40	0.45	0.36
	(0.49)	(0.50)	(0.48)
Ability	0.56	0.36	0.74
	(0.65)	(0.68)	(0.58)
Male	0.44	0.41	0.46
	(0.50)	(0.49)	(0.50)
White	0.71	0.61	0.80
	(0.45)	(0.49)	(0.40)
Never married	0.69	0.65	0.73
	(0.46)	(0.48)	(0.45)
High school GPA	2.58	2.36	2.76
	(1.14)	(1.11)	(1.14)

Table 2. (Continued) Summary Statistics (Completion), 1984–1987 Time Window*

Explanatory Variables	Completion = 0 & 1	Completion = 0	Completion = 1
Father's education	12.19	11.77	12.55
	(3.46)	(3.58)	(3.31)
Mother's education	12.14	11.32	12.85
	(4.88)	(5.04)	(4.63)
Three-year per capita household income average (in log)	8.69	8.60	8.77
	(1.79)	(1.86)	(1.71)
Newspaper, magazine, or library card in household at age 14	0.96	0.95	0.98
	(0.19)	(0.22)	(0.15)
Lived with both parents at age 14	0.78	0.74	0.82
	(0.41)	(0.44)	(0.38)
Unemployment rate	6.73	6.72	6.74
	(3.61)	(3.64)	(3.59)
Age	24.41	25.03	23.87
	(1.94)	(2.09)	(1.62)
Number of observations	2784	1289	1495

GPA = grade point average.

*Note: Values in parentheses are standard errors.

Table 3. Random-Effects Probit College Attendance Estimates, Alternative Time Windows*

Dependent Variable: College Attendance	1982–1985				1983–1986	
	(1)	(2)	(3)	(4)	(5)	(6)
Ability	0.785***			0.635***	0.654***	
	(0.043)			(0.045)	(0.038)	
	[0.048]			[0.037]	[0.039]	
Male	-0.246***			-0.232***	-0.218***	
	(0.048)			(0.048)	(0.043)	
	[-0.015]			[-0.014]	[-0.013]	
White	-0.649***			-0.708***	-0.516***	
	(0.056)			(0.058)	(0.050)	
	[-0.052]			[-0.056]	[-0.038]	
Never married	0.728***			0.687***	0.576***	
	(0.053)			(0.053)	(0.047)	
	[0.043]			[0.039]	[0.035]	
High school GPA	0.571***			0.573***	0.419***	
	(0.042)			(0.042)	(0.037)	
	[0.035]			[0.033]	[0.025]	
Father's education		0.080***		0.045***		0.048***
		(0.011)		(0.010)		(0.009)
		[0.005]		[0.003]		[0.003]
Mother's education		0.080***		0.060***		0.063***
		(0.009)		(0.008)		(0.007)
		[0.005]		[0.003]		[0.004]

1983–1986		1984–1987			
(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	0.535***	0.492***			0.409***
	(0.040)	(0.034)			(0.036)
	[0.031]	[0.032]			[0.026]
	-0.207***	-0.194***			-0.190***
	(0.043)	(0.038)			(0.038)
	[-0.012]	[-0.013]			[-0.012]
	-0.569***	-0.423***			-0.470***
	(0.052)	(0.044)			(0.046)
	[-0.042]	-0.0319647			[-0.035]
	0.552***	0.417***			0.404***
	(0.047)	(0.040)			(0.041)
	[0.032]	[0.028]			[0.026]
	0.420***	0.288***			0.290***
	(0.038)	(0.033)			(0.033)
	[0.024]	[0.019]			[0.018]
	0.025***		0.056***		0.013
	(0.009)		(0.016)		(0.008)
	[0.001]		[0.001]		[0.001]
	0.053***		0.089***		0.042***
	(0.008)		(0.018)		(0.007)
	[0.003]		[0.002]		[0.003]

Table 3. (Continued) Random-Effects Probit College Attendance Estimates, Alternative Time Windows*

Dependent Variable: College Attendance	**1982–1985**				**1983–1986**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Three-year per capita household income average		0.114***		0.026		0.099***
		(0.032)		(0.033)		(0.027)
		[0.007]		[0.001]		[0.007]
Newspaper, magazine, or library card in household at age 14			0.552***	-0.014		
			(0.092)	(0.093)		
			[0.026]	[-0.001]		
Lived with both parents at age 14			0.183***	0.043		
			(0.050)	(0.051)		
			[0.012]	(0.002)		
Unemployment rate	-0.023***	-0.021***	-0.029***	-0.018***	-0.016***	-0.012**
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
	[-0.001]	[-0.001]	[-0.002]	[-0.001]	[-0.001]	[-0.001]
Age	-0.145***	-0.268***	-0.276***	-0.147***	-0.092***	-0.172***
	(0.012)	(0.012)	(0.011)	(0.012)	(0.010)	(0.009)
	[-0.009]	[-0.017]	[-0.019]	[-0.009]	[-0.006]	(-0.012)
Constant	0.797***	2.055***	4.371***	-0.513	0.137	0.826***
	(0.301)	(0.346)	(0.262)	(0.384)	(0.267)	(0.292)
Number of observations	21106	21106	21106	21106	21250	21250
Log likelihood	-5528.794	-5839.158	-6032.458	-5440.206	-5113.357	-5368.083

GPA = grade point average.

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.

1983–1986		1984–1987			
(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	0.033		0.148***		0.039
	(0.029)		(0.044)		(0.026)
	[0.002]		[0.003]		[0.002]
0.435***	0.020			0.486***	-0.000
-0.076	(0.083)			(0.114)	(0.071)
[0.024]	[0.001]			[0.011]	[-0.000]
0.134***	0.048			0.129**	0.036
(0.042)	(0.046)			(0.058)	(0.041)
[0.010]	[0.003]			[0.004]	[0.002]
-0.020***	-0.011	-0.010	-0.011	-0.021**	-0.005
(0.006)	(0.006)	(0.006)	(0.010)	(0.009)	(0.006)
[-0.001]	[-0.001]	[-0.001]	[-0.000]	[-0.001]	[-0.000]
-0.175***	-0.094***	-0.024***	-0.120***	-0.109***	-0.026***
(0.009)	(0.010)	(0.009)	(0.018)	(0.014)	(0.009)
[-0.013]	[-0.005]	[-0.002]	[-0.002]	[-0.004]	[-0.002]
2.519***	-0.972***	-0.919***	-1.621***	0.743***	-1.836***
(0.217)	(0.348)	(0.227)	(0.548)	(0.280)	(0.305)
21250	21250	20518	20518	20518	20518
-5509.493	-5046.058	-4450.582	-4609.549	-4705.008	-4403.544

Table 4. Random-Effects Probit College Attendance Estimates, Alternative Attendance Definitions*

Dependent Variable: College Attendance	Adjusted Definition (1982–1985)	Unadjusted Definition (1979–1982)	Unadjusted Definition (1982–1985)
	(1)	(2)	(3)
Ability	0.635***	0.629***	0.458***
	(0.045)	(0.050)	(0.044)
	[0.037]	[0.042]	[0.019]
Male	-0.232***	-0.258***	-0.059
	(0.048)	(0.054)	(0.047)
	[-0.014]	[-0.017]	[-0.002]
White	-0.708***	-0.719***	-0.452***
	(0.058)	(0.065)	(0.057)
	[-0.056]	[-0.067]	[-0.023]
Never married	0.687***	0.921***	0.574***
	(0.053)	(0.068)	(0.056)
	[0.039]	[0.054]	[0.023]
High school GPA	0.573***	0.524***	0.448***
	(0.042)	(0.047)	(0.042)
	[0.033]	[0.035]	[0.018]
Father's education	0.045***	0.030***	0.030***
	(0.010)	(0.011)	(0.010)
	[0.003]	[0.002]	[0.001]
Mother's education	0.060***	0.048***	0.051***
	(0.008)	(0.009)	(0.008)
	[0.003]	[0.003]	[0.002]
Three-year per capita household income average	0.026	-0.063	0.057
	(0.033)	(0.039)	(0.033)
	[0.001]	[-0.004]	[0.002]
Newspaper, magazine, or library card in household at age 14	-0.014	-0.052	-0.008
	(0.093)	(0.108)	(0.093)
	[-0.001]	[-0.004]	[-0.000]
Lived with both parents at age 14	0.043	0.096	0.106**
	(0.051)	(0.059)	(0.051)
	[0.002]	[0.006]	[0.004]

Table 4. (Continued) Random-Effects Probit College Attendance Estimates, Alternative Attendance Definitions*

Dependent Variable: College Attendance	Adjusted Definition (1982–1985)	Unadjusted Definition (1979–1982)	Unadjusted Definition (1982–1985)
	(1)	**(2)**	**(3)**
Unemployment rate	-0.018***	-0.026***	-0.005
	(0.006)	(0.009)	(0.007)
	[-0.001]	[-0.002]	[-0.000]
Age	-0.147***	-0.237***	-0.254***
	(0.012)	(0.019)	(0.013)
	[-0.009]	[-0.016]	[-0.010]
Constant	-0.513	1.902***	1.200***
	0.384	(0.486)	(0.387)
Number of observations	21106	12072	15659
Log likelihood	-5440.206	-3261.163	-2986.502

GPA = grade point average.

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 5. Random-Effects Probit College Completion Estimates, 1984-1987 Time Window*

Dependent Variable: College Completion	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Faculty-student ratio	10.712*** (3.440) [3.635]						
Instruction spending		0.677*** (0.117) [0.262]					
Research spending			0.066 (0.036) [0.023]				
Academic-related spending				0.544*** (0.094) [0.211]			
Financial aid spending					0.459*** (0.075) [0.178]		
Total spending						0.603*** (0.094) [0.234]	

(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
			8.845***					
			(3.047)					
			[3.306]					
				0.553***				
				(0.121)				
				[0.216]				
					0.023			
					(0.034)			
					[0.008]			
						0.436***		
						(0.097)		
						[0.170]		
							0.479***	
							(0.079)	
							[0.186]	
								0.518***
								(0.098)
								[0.202]

Table 5. (Continued) Random-Effects Probit College Completion Estimates, 1984-1987 Time Window*

Dependent Variable: College Completion	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Public	-1.025***	-1.024***	-1.264***	-1.036***	-0.954***	-1.010***	
	(0.112)	(0.097)	(0.116)	(0.097)	(0.097)	(0.097)	
	[-0.380]	[-0.391]	[-0.468]	[-0.394]	[-0.366]	[-0.386]	
Two-year institution	0.365***	0.448***	0.699***	0.444	0.406	0.445	
	(0.271)	(0.238)	(0.269)	(0.238)	0.239)	(0.238)	
	[0.110]	[0.160]	[0.193]	[0.159]	[0.146]	[0.160]	
Ability							0.374***
							(0.093)
							[0.134]
Male							0.083
							(0.092)
							[0.030]
White							0.374***
							(0.111)
							[0.138]
Never married							0.129
							(0.096)
							[0.047]
High school GPA							0.559***
							(0.085)
							[0.200]

(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
			-0.964***	-1.115***	-1.181***	-1.123***	-1.053***	-1.103***
			(0.099)	(0.102)	(0.103)	(0.102)	(0.102)	(0.102)
			[-0.369]	[-0.420]	[-0.445]	[-0.423]	[-0.400]	[-0.416]
			0.295	0.553**	0.646***	0.545**	0.549**	0.555**
			(0.242)	(0.242)	(0.245)	(0.241)	(0.244)	(0.242)
			[0.104]	[0.195]	[0.205]	[0.192]	[0.193]	[0.195]
		0.299***	0.250***	0.221**	0.201**	0.220**	0.244***	0.217**
		(0.096)	(0.091)	(0.089)	(0.092)	(0.089)	(0.090)	(0.089)
		[0.107]	[0.093]	[0.086]	[0.075]	[0.086]	[0.095]	[0.085]
		0.101	0.114	0.036	0.067	0.036	0.024	0.029
		(0.093)	(0.088)	(0.087)	(0.090)	(0.087)	(0.087)	(0.087)
		[0.036]	[0.042]	[0.014]	[0.025]	[0.014]	[0.009]	[0.011]
		0.319***	0.300***	0.247**	0.296***	0.240**	0.282***	0.252**
		(0.116)	(0.111)	(0.109)	(0.112)	(0.108)	(0.110)	(0.109)
		[0.117]	[0.114]	[0.097]	[0.113]	[0.094]	[0.110]	[0.099]
		0.140	0.150	0.107	0.118	0.104	0.117	0.100
		(0.097)	(0.094)	(0.093)	(0.095)	(0.093)	(0.093)	(0.093)
		[0.051]	[0.057]	[0.042]	[0.044]	[0.041]	[0.046]	[0.039]
		0.569***	0.612***	0.538***	0.575***	0.537***	0.551***	0.543***
		(0.086)	(0.083)	(0.082)	(0.084)	(0.082)	(0.083)	(0.082)
		[0.203]	[0.229]	[0.210]	[0.215]	[0.209]	[0.214]	[0.211]

Table 5. (Continued) Random-Effects Probit College Completion Estimates, 1984-1987 Time Window*

Dependent Variable: College Completion	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Father's education							
Mother's education							
Three-year per capita household income average							
Newspaper, magazine, or library card in household at age 14							
Lived with both parents at age 14							
Unemployment rate							-0.035** (0.015) [-0.041]

(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
0.034		0.029	0.024	0.024	0.032	0.023	0.021	0.021
(0.018)		(0.018)	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)
[0.012]		[0.010]	[0.009]	[0.009]	[0.012]	[0.009]	[0.008]	[0.008]
0.037***		0.008	0.015	0.006	0.007	0.007	0.006	0.007
(0.014)		(0.014)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)
[0.013]		[0.003]	[0.006]	[0.002]	[0.003]	[0.003]	[0.002]	[0.003]
0.248***		0.123**	0.079	0.081	0.089	0.082	0.094	0.079
(0.059)		(0.061)	(0.059)	(0.058)	(0.060)	(0.058)	(0.058)	(0.058)
[0.088]		[0.044]	[0.030]	[0.032]	[0.033]	[0.032]	[0.037]	[0.031]
	0.544**	0.035	-0.076	-0.009	0.028	-0.009	0.043	-0.018
	(0.224)	(0.238)	(0.223)	(0.217)	(0.225)	(0.217)	(0.219)	(0.217)
	[0.209]	[0.013]	[-0.028]	[-0.003]	[0.011]	[-0.004]	[0.017]	[-0.007]
	0.372***	0.115	0.082	0.153	0.123	0.149	0.148	0.160
	(0.103)	(0.110)	(0.105)	(0.103)	(0.106)	(0.103)	(0.103)	(0.103)
	[0.138]	[0.042]	[0.031]	[0.060]	[0.047]	[0.059]	[0.058]	[0.063]
-0.021	-0.031**	-0.030**	-0.012	-0.010	-0.014	-0.009	-0.012	-0.009
(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)	(0.014)	(0.015)	(0.014)
[-0.007]	[-0.011]	[-0.011]	[-0.005]	[-0.004]	[-0.005]	[-0.004]	[-0.005]	[-0.003]

Table 5. (Continued) Random-Effects Probit College Completion Estimates, 1984-1987 Time Window*

Dependent Variable: College Completion	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Age							-0.114***
							(0.024)
							[-0.013]
Constant	1.950***	1.113***	2.914***	1.352***	2.530***	0.671	1.798***
	(0.257)	(0.379)	(0.154)	(0.339)	(0.174)	(0.408)	(0.689)
Number of observations	2784	2784	2784	2784	2784	2784	2784
Log likelihood	-1437.855	-1280.933	-1352.445	-1280.669	-1280.083	-1276.382	-1443.391

GPA = grade point average.

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.

(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
-0.180***	-0.166***	-0.124***	-0.102***	-0.059**	-0.091***	-0.060**	-0.053**	-0.056**
(0.023)	(0.022)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
[-0.064]	[-0.059]	[-0.044]	[-0.038]	[-0.023]	[-0.034]	[-0.023]	[-0.021]	[-0.022]
2.428***	4.469***	0.317	0.811	-0.261	1.372	-0.030	0.427	-0.773
(0.708)	(0.592)	(0.856)	(0.839)	(0.917)	(0.822)	(0.897)	(0.847)	(0.939)
2784	2784	2784	2784	2784	2784	2784	2784	2784
-1508.400	-1526.995	-1436.498	-1329.995	-1187.880	-1259.452	-1188.308	-1179.242	-1183.760

Table 6. Random-Effects Probit College Completion School Resource Estimators, Alternative Completion Definitions*

Dependent Variable: College Completion	Adjusted Definition (1984–1987) (1)	Unadjusted Definition (1984–1987) (2)
Faculty-student ratio	10.712***	7.890***
	(3.440)	(2.595)
	[3.635]	[2.918]
Instruction spending	0.677***	0.405***
	(0.117)	(0.105)
	[0.262]	[0.143]
Research spending	0.066	0.008
	(0.036)	(0.029)
	[0.023]	[0.003]
Academic-related spending	0.544***	0.317***
	(0.094)	(0.083)
	[0.211]	[0.112]
Financial aid spending	0.459***	0.376***
	(0.075)	(0.070)
	[0.178]	[0.133]
Total spending	0.603***	0.383***
	(0.094)	(0.083)
	[0.234]	[0.135]
Statistically significant student background characteristics	Ability, white, HS GPA	HS GPA; also, ability and marital status for faculty-student ratio
Number of observations	2784	1679

HS GPA = high school grade point average.
*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 7. Random-Effects Probit College Completion School Resource Estimators, Alternative Time Windows*

School Resource Indicators	**1984–1987 (1)**	**1985–1988 (2)**	**1986–1989 (3)**
Faculty-student ratio	8.845***	10.140***	8.955***
	(3.047)	(2.802)	(2.857)
	[3.306]	[3.950]	[3.403]
Instruction spending	0.553***	0.643***	0.395**
	(0.121)	(0.125)	(0.121)
	[0.216]	[0.238]	[0.155]
Research spending	0.023	0.057	0.031
	(0.034)	(0.034)	(0.038)
	[0.008]	[0.021]	[0.012]
Academic-related spending	0.436***	0.521***	0.336***
	(0.097)	(0.101)	(0.100)
	[0.170]	[0.193]	[0.132]
Financial aid spending	0.479***	0.551***	0.465***
	(0.079)	(0.083)	(0.081)
	[0.186]	[0.204]	[0.182]
Total spending	0.518***	0.587***	0.436***
	(0.098)	(0.101)	(0.101)
	[0.202]	[0.218]	[0.171]
Number of observations	2784	2910	2990

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 8. College Completion Baseline Random-Effects Probit Ability Estimators*

Time Window	School Resource Indicator in Econometric Specification						
	None (1)	Faculty-student ratio (2)	Instruction spending (3)	Research spending (4)	Academic-related spending (5)	Financial aid spending (6)	Total spending (7)
1984–1987	0.299***	0.250***	0.221**	0.201**	0.220**	0.244***	0.217**
	(0.096)	(0.091)	(0.089)	(0.092)	(0.089)	(0.090)	(0.089)
	[0.107]	[0.093]	[0.086]	[0.075]	[0.086]	[0.095]	[0.085]
Hausman test p-value		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
1985–1988	0.383***	0.320***	0.331***	0.325***	0.328***	0.366***	0.329***
	(0.098)	(0.090)	(0.102)	(0.103)	(0.102)	(0.102)	[0.102]
	[0.140]	[0.125]	[0.123]	[0.119]	[0.193]	[0.135]	(0.122)
Hausman test p-value		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
1986–1989	0.395***	0.405***	0.336***	0.369***	0.334***	0.359***	0.335***
	(0.096)	(0.102)	(0.092)	(0.101)	(0.093)	(0.093)	(0.092)
	[0.151]	[0.154]	[0.132]	[0.141]	[0.131]	[0.140]	[0.131]
Hausman test p-value		*0.226*	*0.000*	*0.580*	*0.000*	*0.000*	*0.000*

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 9. Two-Step IV Reduced-Form Equation Estimates (Completion)*

Instrumental Variable	Endogenous Variable					
	Faculty-student ratio	**Instruction spending**	**Research spending**	**Academic-related spending**	**Financial aid spending**	**Total spending**
Faculty-student ratio		12.568***	17.392***	14.386***	14.892***	17.448***
		(2.193)	(2.416)	(2.458)	(1.886)	(3.013)
Instruction spending	0.018***		2.197***	1.201***	0.797***	1.1717***
	(0.003)		(0.094)	(0.014)	(0.055)	(0.022)
Research spending	0.002***	0.136***		0.217***	0.075***	0.195***
	(0.000)	(0.008)		(0.008)	(0.013)	(0.010)
Academic-related spending	0.013***	0.764***	2.156***		0.582***	0.950***
	(0.002)	(0.010)	(0.066)		(0.041)	(0.013)
Financial aid spending	0.010***	0.302***	0.414***	0.348***		0.485***
	(0.001)	(0.019)	(0.065)	(0.023)		(0.019)
Total spending	0.016***	0.726***	1.891***	0.926***	0.792***	
	(0.002)	(0.013)	(0.072)	(0.014)	(0.040)	
Administrative staff-student ratio	1.106***	19.405***	23.800***	21.881***	21.486**	28.255***
	(0.187)	(5.091)	(6.682)	(5.945)	(8.558)	(6.448)
Number of observations	2784	2784	2784	2784	2784	2784

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 10. Two-Step IV Wald Test on School Resource Indicators (Completion)*

Instrumental Variable	Endogenous Variable					
	Faculty-student ratio	**Instruction spending**	**Research spending**	**Academic-related spending**	**Financial aid spending**	**Total spending**
Faculty-student ratio		-0.342***	-0.773***	-0.314***	-0.446***	-0.236***
		(0.095)	(0.181)	(0.086)	(0.155)	(0.070)
Instruction spending	-70.298***		-0.101	-0.343	-0.383**	0.242
	(4.853)		(0.078)	(0.346)	(0.167)	(0.260)
Research spending	-76.943***	-0.048		-0.016	-0.414***	-0.025
	(6.237)	(0.069)		(0.066)	(0.135)	(0.050)
Academic-related spending	-72.925***	-0.155	-0.038		-0.428**	0.483
	(4.987)	(0.437)	(0.029)		(0.180)	(0.298)
Financial aid spending	-78.542***	-1.069***	-1.898***	-0.964***		-0.628***
	(5.201)	(0.242)	(0.180)	(0.211)		(0.170)
Total spending	-69.202***	-0.997***	-0.286***	-1.018***	-0.344**	
	(4.729)	(0.335)	(0.076)	(0.304)	(0.146)	
Administrative staff-student ratio	-15.058	-0.344***	-1.853***	-0.316***	-0.551***	-0.242***
	(9.349)	(0.099)	(0.330)	(0.089)	(0.191)	(0.073)

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.
Shaded cells also reject H_o: no endogeneity in a Wald test for MLE.

Table 11. List of Valid Instruments (Completion)

Endogenous Variable	Valid Instruments		
	Two-Step IV (1)	Standard ML (2)	Papke & Wooldridge ML (3)
Faculty-student ratio	Instruction, research, academic-related, financial aid, and total spending	Instruction, research, academic-related, financial aid, and total spending	Instruction, research, academic-related, and total spending
Instruction spending	Faculty-student and administrative staff-student ratios; financial aid spending	Financial aid spending	Financial aid spending
Research spending	Faculty-student and administrative staff-student ratios; financial aid spending	Faculty-student and administrative staff-student ratios; financial aid spending	Faculty-student ratio, financial aid spending
Academic-related spending	Faculty-student and administrative staff-student ratios; financial aid spending	Financial aid spending	Financial aid spending
Financial aid spending	Faculty-student and administrative staff-student ratios; instruction, research, and academic-related spending	Academic-related spending	None
Total spending	Faculty-student and administrative staff-student ratios	None	None

Table 12. School Resource Estimated Coefficients (Completion), Alternative IV Methodologies*

School Resource Indicators	**Random-effects probit (1984–1987)**	**Random-effects probit (1984–1987), time-constant unobserved het.**	**Two-step (minimum)**	**Two-step (maximum)**
	(1)	**(2)**	**(3)**	**(4)**
Faculty-student ratio	8.845***	8.984***	65.540***	83.532***
	(3.047)	(3.055)	(5.193)	(6.932)
	[3.306]	[3.354]	[25.157]	[31.686]
Instrumental variable			*Total spending*	*Research*
Instruction spending	0.553***	0.546***	0.828***	1.419***
	(0.121)	(0.122)	(0.146)	(0.237)
	[0.216]	[0.213]	[0.324]	[0.552]
Instrumental variable			*Faculty-per-student*	*Financial aid*
Research spending	0.023	0.016	0.776***	1.870***
	(0.034)	(0.034)	(0.181)	(0.179)
	[0.008]	[0.006]	[0.292]	[0.712]
Instrumental variable			*Faculty-per-student*	*Financial aid*
Academic-related spending	0.436***	0.427***	0.699***	1.244***
	(0.097)	(0.098)	(0.123)	(0.207)
	[0.170]	[0.166]	[0.273]	[0.484]
Instrumental variable			*Faculty-per-student*	*Financial aid*

Standard ML Estimator (minimum)	**Standard ML Estimator (maximum)**	**Papke & Wooldridge ML Estimator (maximum)**
(5)	**(6)**	**(7)**
56.386***	81.719***	91.196***
(10.650)	(7.048)	(6.435)
[22.468]	[32.598]	[36.382]
Total spending	*Research*	*Total spending*
	1.209***	0.954***
	(0.197)	(0.285)
	[0.482]	[0.380]
	Financial aid	*Financial aid*
0.628***	0.902***	0.944***
(0.196)	(0.037)	(0.027)
[0.250]	[0.360]	[0.377]
Faculty-per-student	*Financial aid*	*Financial aid*
	1.041***	0.827***
	(0.169)	(0.247)
	[0.415]	[0.330]
	Financial aid	*Financial aid*

Table 12. (Continued) School Resource Estimated Coefficients (Completion), Alternative IV Methodologies*

School Resource Indicators	**Random-effects probit (1984–1987)**	**Random-effects probit (1984–1987), time-constant unobserved het.**	**Two-step (minimum)**	**Two-step (maximum)**
	(1)	**(2)**	**(3)**	**(4)**
Financial aid spending	0.479***	0.494***	0.832***	0.981***
	(0.079)	(0.079)	(0.170)	(0.195)
	[0.186]	[0.192]	[0.323]	[0.383]
Instrumental variable			*Academic-related*	*Admin-per-student*
Total spending	0.518***	0.515***	0.699***	0.719***
	(0.098)	(0.098)	(0.114)	(0.118)
	[0.202]	[0.201]	[0.273]	[0.281]
Instrumental variable			*Faculty-per-student*	*Admin-per-student*
Number of observations	2784	2784	2784	2784

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.
Minimum and maximum values reported are based on marginal effects.
Shaded regions indicate that no valid instrument could be obtained for the endogenous resource indicator, so an invalid instrument was used in the reported estimates.
Due to low intertemporal variation in school resource indicators, the random-effects probit and Papke and Wooldridge ML estimations incorporating time-constant unobserved heterogeneity include only averages of household income and local labor market unemployment rate as additional explanatory variables.

Standard ML Estimator (minimum)	**Standard ML Estimator (maximum)**	**Papke & Wooldridge ML Estimator (maximum)**
(5)	**(6)**	**(7)**
	0.618***	0.384
	(0.145)	(0.218)
	[0.246]	[0.153]
	Academic-related	*Academic-related*
	0.598***	2.125**
	(0.223)	(0.913)
	[0.238]	[0.848]
	Faculty-per-student	*Admin-per-student*
2784	2784	2784

Table 13. School Resource Marginal Effects at Different Percentiles of the Resource Distribution (Completion)*

Percentile	Faculty-student ratio (1)	Instruction spending (2)	Research spending (3)	Academic-related spending (4)	Financial aid spending (5)	Total spending (6)
5th	22.149***	0.191***	0.005***	0.182***	0.241***	0.102***
	(0.445)	(0.023)	(0.001)	(0.012)	(0.054)	(0.016)
10th	9.257***	0.144***	0.042***	0.149***	0.246***	0.077***
	(1.289)	(0.042)	(0.005)	(0.026)	(0.058)	(0.018)
25th	1.192**	0.090	0.271***	0.100**	0.235***	0.048***
	(0.519)	(0.051)	(0.005)	(0.041)	(0.050)	(0.018)
50th	0.074	0.057	0.329***	0.066	0.206***	0.028
	(0.062)	(0.048)	(0.009)	(0.044)	(0.032)	(0.015)
75th	0.001	0.031	0.029***	0.028	0.163***	0.014
	(0.001)	(0.037)	(0.003)	(0.033)	(0.008)	(0.011)
90th	0.000	0.016	0.007***	0.014	0.110***	0.007
	(0.000)	(0.026)	(0.001)	(0.022)	(0.016)	(0.007)
95th	0.000	0.007	0.002***	0.006	0.082***	0.003
	(0.000)	(0.015)	(0.001)	(0.013)	(0.023)	(0.004)
Instrument	*Total spending*	*Financial aid*	*Financial aid*	*Financial aid*	*Academic-related*	*Admin-per-student*

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 14. Summary Statistics (Persistence), 1984-1989 Time Window*

Explanatory Variables	Persist = 0 & 1	Persist = 0	Persist = 1
Faculty-student ratio (in log)	0.01	0.01	0.02
	(0.02)	(0.02)	(0.03)
Instruction spending (in log)	0.68	0.36	1.86
	(1.26)	(0.95)	(1.54)
Research spending (in log)	0.06	0.00	0.26
	(0.89)	(0.61)	(1.51)
Academic-related spending (in log)	0.75	0.39	2.05
	(1.39)	(1.04)	(1.72)
Financial aid spending (in log)	0.28	0.12	0.86
	(0.69)	(0.47)	(0.98)
Total spending (in log)	0.92	0.48	2.52
	(1.71)	(1.28)	(2.08)
Public institution	0.19	0.13	0.44
	(0.40)	(0.33)	(0.50)
Two-year institution	0.06	0.06	0.07
	(0.24)	(0.23)	(0.26)
Northeast	0.18	0.18	0.19
	(0.38)	(0.38)	(0.39)
North Central	0.22	0.20	0.26
	(0.41)	(0.40)	(0.44)
West	0.22	0.23	0.18
	(0.41)	(0.42)	(0.39)
South	0.37	0.38	0.35
	(0.48)	(0.48)	(0.48)
Ability	0.30	0.21	0.61
	(0.69)	(0.67)	(0.65)
Male	0.45	0.44	0.49
	(0.50)	(0.50)	(0.50)
White	0.66	0.63	0.74
	(0.47)	(0.48)	(0.44)
Never married	0.56	0.49	0.81
	(0.50)	(0.50)	(0.39)
High school GPA	2.21	2.13	2.50
	(1.17)	(1.14)	(1.23)

Table 14. (Continued) Summary Statistics (Persistence), 1984-1989 Time Window*

Explanatory Variables	Persist = 0 & 1	Persist = 0	Persist = 1
Father's education	11.32	11.12	12.04
	(3.66)	(3.64)	(3.63)
Mother's education	10.80	10.46	12.04
	(5.13)	(5.12)	(4.97)
Three-year per capita household income average (in log)	8.68	8.73	8.48
	(1.75)	(1.70)	(1.93)
Newspaper, magazine, or library card in household at age 14	0.94	0.94	0.96
	(0.23)	(0.24)	(0.19)
Lived with both parents at age 14	0.72	0.71	0.75
	(0.45)	(0.45)	(0.43)
Unemployment rate	6.52	6.47	6.72
	(3.49)	(3.43)	(3.67)
Age	25.12	25.75	22.87
	(2.90)	(2.71)	(2.38)
Number of observations	14546	11395	3151

GPA = grade point average.

*Note: Values in parentheses are standard errors.

Table 15. Random-Effects Probit College Persistence Estimates, 1984-1989 Time Window*

Dependent Variable: College Persistence	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Faculty-student ratio	8.128*** (1.441) [1.798]						
Instruction spending		0.550*** (0.047) [0.110]					
Research spending			0.067*** (0.016) [0.015]				
Academic-related spending				0.456*** (0.040) [0.092]			
Financial aid spending					0.351*** (0.029) [0.071]		
Total spending						0.494*** (0.038) [0.099]	

(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
			5.790***					
			(1.386)					
			[1.172]					
				0.392***				
				(0.047)				
				[0.073]				
					0.0379**			
					(0.016)			
					[0.008]			
						0.319***		
						(0.039)		
						[0.060]		
							0.2842***	
							(0.028)	
							[0.054]	
								0.367***
								(0.037)
								[0.069]

Table 15. (Continued) Random-Effects Probit College Persistence Estimates, 1984-1989 Time Window*

Dependent Variable: College Persistence	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Public	0.968***	0.670***	0.736***	0.667***	0.718***	0.672***	
	(0.043)	(0.041)	(0.045)	(0.042)	(0.041)	(0.041)	
	[0.279]	[0.167]	[0.200]	[0.166]	[0.183]	[0.168]	
Two-year institution	-0.551***	-0.448***	-0.324***	-0.447***	-0.495***	-0.428***	
	(0.071)	(0.067)	(0.071)	(0.067)	(0.066)	(0.066)	
	[-0.092]	[-0.070]	[-0.060]	[-0.070]	[-0.077]	[-0.068]	
Ability							0.500***
							(0.049)
							[0.101]
Male							-0.053
							(0.052)
							[-0.011]
White							-0.050
							(0.060)
							[-0.010]
Never married							0.574***
							(0.049)
							[0.111]
High school GPA							0.455***
							(0.047)
							[0.092]

(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
			0.698***	0.447***	0.503***	0.445***	0.489***	0.450***
			(0.042)	(0.041)	(0.044)	(0.041)	(0.040)	(0.041)
			[0.177]	[0.098]	[0.121]	[0.098]	[0.110]	[0.099]
			-0.371***	-0.291***	-0.153**	-0.293***	-0.315***	-0.272***
			(0.068)	(0.066)	(0.069)	(0.066)	(0.064)	(0.065)
			[-0.061]	[-0.046]	[-0.029]	[-0.046]	[-0.050]	[-0.044]
		0.461***	0.321***	0.229***	0.267***	0.227***	0.232***	0.224***
		(0.051)	(0.040)	(0.036)	(0.041)	(0.037)	(0.036)	(0.036)
		[0.093]	[0.065]	[0.043]	[0.054]	[0.043]	[0.044]	[0.042]
		-0.034	-0.034	-0.037	-0.047	-0.036	-0.043	-0.0390
		(0.052)	(0.040)	(0.037)	(0.041)	(0.037)	(0.037)	(0.037)
		[-0.007]	[-0.007]	[-0.007]	[-0.010]	[-0.007]	[-0.008]	[-0.007]
		-0.026	0.002	0.010	0.018	0.007	0.016	0.012
		(0.062)	(0.049)	(0.045)	(0.050)	(0.045)	(0.044)	(0.044)
		[-0.005]	[0.000]	[0.002]	[0.004]	[0.001]	[0.003]	[0.002]
		0.546***	0.385***	0.276***	0.342***	0.275***	0.272***	0.267***
		(0.049)	(0.042)	(0.040)	(0.043)	(0.040)	(0.040)	(0.040)
		[0.106]	[0.076]	[0.051]	[0.068]	[0.051]	[0.050]	[0.049]
		0.446***	0.315***	0.242***	0.284***	0.242***	0.242***	0.238***
		(0.046)	(0.037)	(0.034)	(0.037)	(0.034)	(0.033)	(0.033)
		[0.090]	[0.064]	[0.045]	[0.058]	[0.045]	[0.046]	[0.045]

Table 15. (Continued) Random-Effects Probit College Persistence Estimates, 1984-1989 Time Window*

Dependent Variable: College Persistence	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father's education							
Mother's education							
Three-year per capita household income average							
Newspaper, magazine, or library card in household at age 14							
Lived with both parents at age 14							
Unemployment rate							-0.016** (0.008) [-0.003]

(8)	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
0.046***		0.026**	0.021***	0.016**	0.019**	0.016**	0.016**	0.015**
(0.011)		(0.010)	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
[0.010]		[0.005]	[0.004]	[0.003]	[0.004]	[0.003]	[0.003]	[0.003]
0.049***		0.022***	0.012	0.008	0.010	0.008	0.008	0.008
(0.009)		(0.008)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
(0.010)		[0.004]	[0.002]	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]
-0.092***		-0.143***	-0.102***	-0.083***	-0.098***	-0.082***	-0.073***	-0.082***
(0.030)		(0.030)	(0.025)	(0.024)	(0.026)	(0.024)	(0.024)	(0.024)
[-0.019]		[-0.029]	[-0.021]	[-0.016]	[-0.020]	[-0.015]	[-0.014]	[-0.015]
	0.391***	-0.046	-0.013	-0.006	0.014	-0.006	0.009	-0.009
	(0.117)	(0.114)	(0.089)	(0.083)	(0.091)	(0.083)	(0.082)	(0.082)
	[0.067]	[-0.009]	[-0.003]	[-0.001]	[0.003]	[-0.001]	[0.002]	[-0.002]
	0.217***	0.046	0.049	0.049	0.049	0.049	0.058	0.052
	(0.058)	(0.058)	(0.045)	(0.041)	(0.046)	(0.041)	(0.041)	(0.041)
	[0.043]	[0.009]	[0.010]	[0.009]	[0.010]	[0.009]	[0.011]	[0.010]
-0.014	-0.019**	-0.015	-0.014**	-0.012	-0.014**	-0.011	-0.015**	-0.012
(0.008)	(0.008)	(0.008)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
[-0.003]	[-0.004]	[-0.003]	[-0.003]	[-0.002]	[-0.003]	[-0.002]	[-0.003]	[-0.002]

Table 15. (Continued) Random-Effects Probit College Persistence Estimates, 1984-1989 Time Window*

Dependent Variable: College Persistence	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Age							-0.252*** (0.012) [-0.051]
Constant	-0.083 (0.097)	-0.504*** (0.148)	0.754*** (0.064)	-0.356*** (0.138)	0.653*** (0.067)	-0.855*** (0.159)	3.465*** (0.326)
Number of observations	14546	14546	14546	14546	14546	14546	14546
Log likelihood	-5729.755	-5014.223	-5443.063	-5015.3789	-5014.448	-4995.426	-5488.109

GPA = grade point average.

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.

(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
-0.322***	-0.337***	-0.244***	-0.172***	-0.149***	-0.176***	-0.149***	-0.145***	-0.148***
(0.013)	(0.013)	(0.012)	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)
[-0.067]	[-0.071]	[-0.049]	[-0.035]	[-0.028]	[-0.036]	[-0.028]	[-0.027]	[-0.028]
6.560***	6.737***	4.011***	3.126***	2.737***	4.006***	2.857***	3.338***	2.417
(0.382)	(0.311)	(0.415)	(0.348)	(0.345)	(0.351)	(0.342)	(0.321)	(0.348)
14546	14546	14546	14546	14546	14546	14546	14546	14546
-5694.983	-5746.623	-5463.7104	-5177.630	-4616.416	-4982.918	-4618.435	-4607.755	-4602.537

Table 16. Random-Effects Probit College Persistence School Resource Estimators, Alternative Persistence Definitions*

Dependent Variable: College Persistence	Grades 13 to 16 (1)	Grades 13 to 15 (2)	Grade 13 to 14 (3)	Grade 14 to 15 (4)
Faculty-student ratio	5.790***	5.471***	5.094	7.699***
	(1.386)	(1.804)	(5.582)	(2.876)
	[1.172]	[0.917]	[1.043]	[1.571]
Instruction spending	0.392***	0.414***	0.383***	0.571***
	(0.047)	(0.060)	(0.112)	(0.102)
	[0.073]	[0.063]	[0.072]	[0.103]
Research spending	0.038**	0.068***	0.064	0.073**
	(0.016)	(0.020)	(0.042)	(0.029)
	[0.008]	[0.011]	[0.013]	[0.015]
Academic-related spending	0.319***	0.359***	0.329***	0.485***
	(0.039)	(0.051)	(0.099)	(0.085)
	[0.060]	[0.054]	[0.062]	[0.088]
Financial aid spending	0.284***	0.267***	0.210***	0.417***
	(0.028)	(0.034)	(0.061)	(0.060)
	[0.054]	[0.041]	[0.039]	[0.077]
Total spending	0.367***	0.387***	0.335***	0.545***
	(0.037)	(0.047)	(0.091)	(0.080)
	[0.069]	[0.059]	[0.064]	[0.099]
Statistically significant student background characteristics	Ability, marital status, HS GPA, income (-), father's education	Ability, marital status, HS GPA, income (-), father's education (excl. instruction, academic, and total spending)	Ability, marital status, HS GPA	Ability (excl. research, academic, and total spending), marital status, HS GPA, income (-), father's education
Number of observations	14546	11399	4161	3849

HS GPA = high school grade point average.
*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 17. Random-Effects Probit College Persistence School Resource Estimators, Alternative Time Windows*

School Resource Indicators	1984-1989	1985-1990	1986-1991
	(1)	(2)	(3)
Faculty-student ratio	5.790***	4.600***	5.316***
	(1.386)	(1.068)	(0.949)
	[1.172]	[0.739]	[0.671]
Instruction spending	0.392***	0.449***	0.368***
	(0.047)	(0.044)	(0.047)
	[0.073]	[0.066]	[0.042]
Research spending	0.038**	0.051***	0.053***
	(0.016)	(0.014)	(0.016)
	[0.008]	[0.008]	[0.007]
Academic-related spending	0.319***	0.364***	0.307***
	(0.039)	(0.037)	(0.040)
	[0.060]	[0.053]	[0.035]
Financial aid spending	0.284***	0.289***	0.246***
	(0.028)	(0.026)	(0.028)
	[0.054]	[0.042]	[0.028]
Total spending	0.367***	0.405***	0.345***
	(0.037)	(0.035)	(0.038)
	[0.069]	[0.059]	[0.039]
Number of observations	14546	13999	13250

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 18. College Persistence Baseline Random-Effects Probit Ability Estimators*

Time Window	School Resource Indicator in Econometric Specification						
	None	**Faculty-student ratio**	**Instruction spending**	**Research spending**	**Academic-related spending**	**Financial aid spending**	**Total spending**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
1984-1989	0.461***	0.321***	0.229***	0.267***	0.227***	0.232***	0.224***
	(0.051)	(0.040)	(0.036)	(0.041)	(0.037)	(0.036)	(0.036)
	[0.093]	[0.065]	[0.043]	[0.054]	[0.043]	[0.044]	[0.042]
Hausman Test p-value		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
1985-1990	0.437***	0.292***	0.185***	0.218***	0.183***	0.201***	0.183***
	(0.053)	(0.039)	(0.038)	(0.040)	(0.038)	(0.037)	(0.037)
	[0.067]	[0.047]	[0.027]	[0.036]	[0.027]	[0.029]	[0.027]
Hausman Test p-value		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
1986-1991	0.407***	0.223***	0.165***	0.202***	0.307***	0.176***	0.162***
	(0.055)	(0.038)	(0.039)	(0.041)	(0.040)	(0.038)	(0.039)
	[0.044]	[0.028]	[0.019]	[0.025]	[0.018]	[0.020]	[0.018]
Hausman Test p-value		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 19. Two-Step IV Reduced-Form Equation Estimates (Persistence)*

Instrumental Variable	Endogenous Variable					
	Faculty-student ratio	**Instruction spending**	**Research spending**	**Academic-related spending**	**Financial aid spending**	**Total spending**
Faculty-student ratio		14.192***	14.346***	16.159***	14.382***	19.275***
		(1.827)	(1.629)	(2.048)	(1.485)	(2.476)
Instruction spending	0.013***		1.662***	1.159***	1.004***	1.181***
	(0.001)		(0.046)	(0.006)	(0.025)	(0.009)
Research spending	0.002***	0.147***		0.219***	0.099***	0.206***
	(0.000)	(0.004)		(0.005)	(0.007)	(0.006)
Academic-related spending	0.011***	0.806***	1.698***		0.789***	1.000***
	(0.001)	(0.005)	(0.034)		(0.020)	(0.006)
Financial aid spending	0.007***	0.360***	0.405***	0.408***		0.532***
	(0.000)	(0.008)	(0.028)	(0.010)		(0.009)
Total spending	0.011***	0.743***	1.447***	0.905***	0.934***	
	(0.001)	(0.005)	(0.036)	(0.006)	(0.019)	
Administrative staff-student ratio	1.338***	31.767***	27.464***	35.678***	31.625***	44.613***
	(0.169)	(6.394)	(5.021)	(7.277)	(7.638)	(8.346)
Number of observations	14546	14546	14546	14546	14546	14546

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 20. Two-Step IV Wald Test on School Resource Indicators (Persistence)*

Instrumental Variable	Endogenous Variable					
	Faculty-student ratio	Instruction spending	Research spending	Academic-related spending	Financial aid spending	Total spending
Faculty-student ratio		-0.238***	-0.583***	-0.218***	-0.359***	-0.166***
		(0.038)	(0.100)	(0.034)	(0.066)	(0.028)
Instruction spending	-61.632***		0.109***	-0.313**	-0.201***	0.270**
	(2.002)		(0.042)	(0.155)	(0.056)	(0.111)
Research spending	-55.342***	0.022		0.034	-0.102**	0.032
	(2.456)	(0.026)		(0.025)	(0.045)	(0.019)
Academic-related spending	-62.579***	-0.031	0.191***		-0.215***	0.498***
	(2.031)	(0.187)	(0.039)		(0.058)	(0.124)
Financial aid spending	-64.991***	-0.443***	-0.890***	-0.414***		-0.224***
	(2.038)	(0.085)	(0.079)	(0.074)		(0.064)
Total spending	-62.035***	-0.812***	-0.001	-0.901***	-0.241***	
	(1.982)	(0.140)	(0.039)	(0.131)	(0.054)	
Administrative staff-student ratio	-19.212***	-0.268***	-1.331***	-0.247***	-0.477***	-0.188***
	(3.777)	(0.038)	(0.145)	(0.035)	(0.074)	(0.028)

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.
Shaded cells also reject H_o: no endogeneity in a Wald test for MLE.

Table 21. List of Valid Instruments (Persistence)

Endogenous Variable	Valid Instruments		
	Two-Step IV (1)	Standard ML (2)	Papke & Wooldridge ML (3)
Faculty-student ratio	Administrative staff-student ratio; instruction, research, academic-related, financial aid, and total spending	Instruction, research, academic-related, financial aid, and total spending	Research spending
Instruction spending	Faculty-student and administrative staff-student ratios; financial aid spending	Faculty-student and administrative staff-student ratios; financial aid spending	Administrative staff-student ratio
Research spending	Faculty-student and administrative staff-student ratios; financial aid spending	Administrative staff-student ratio and financial aid spending	Administrative staff-student ratio and financial aid spending
Academic-related spending	Faculty-student and administrative staff-student ratios; financial aid spending	Faculty-student and administrative staff-student ratios; financial aid spending	Administrative staff-student ratio
Financial aid spending	Faculty-student and administrative staff-student ratios; instruction, research, and academic-related spending	Faculty-student and administrative staff-student ratios; instruction and research spending	None
Total spending	Faculty-student and administrative staff-student ratios	Administrative staff-student ratio	Administrative staff-student ratio

Table 22. School Resource Estimated Coefficients (Persistence), Alternative IV Methodologies*

School Resource Indicators	**Random-effects probit (1984–1989)**	**Random-effects probit (1984–1989), time-constant unobserved het.**	**Two-step (minimum)**	**Two-step (maximum)**
	(1)	**(2)**	**(3)**	**(4)**
Faculty-student ratio	5.790***	5.814***	59.180***	64.247***
	(1.386)	(1.383)	(2.268)	(2.339)
	[1.172]	[1.179]	[11.333]	[12.222]
Instrumental variable			*Total spending*	*Financial aid*
Instruction spending	0.392***	0.392***	0.582***	0.680***
	(0.047)	(0.047)	(0.056)	(0.073)
	[0.073]	[0.073]	[0.107]	[0.128]
Instrumental variable			*Faculty-per-student*	*Financial aid*
Research spending	0.038**	0.037***	0.610***	1.354***
	(0.016)	(0.016)	(0.100)	(0.144)
	[0.008]	[0.008]	[0.124]	[0.276]
Instrumental variable			*Faculty-per-student*	*Admin-per-student*
Academic-related spending	0.319***	0.319***	0.499***	0.605***
	(0.039)	(0.039)	(0.049)	(0.064)
	[0.060]	[0.060]	[0.092]	[0.114]
Instrumental variable			*Faculty-per-student*	*Financial aid*

(5)	**(6)**	**(7)**
80.903***	93.955***	101.570***
(6.881)	(5.272)	(5.557)
[24.679]	[32.202]	[37.311]
Total spending	*Financial aid*	*Research*
0.745***	1.566***	1.605**
(0.179)	(0.335)	(0.517)
[0.149]	[0.334]	[0.334]
Faculty-per-student	*Admin-per-student*	*Admin-per-student*
1.007***	1.066***	1.073***
(0.065)	(0.058)	(0.106)
[0.346]	[0.388]	[0.390]
Admin-per-student	*Financial aid*	*Financial aid*
0.630***	1.342***	1.384***
(0.153)	(0.294)	(0.449)
[0.126]	[0.289]	[0.291]
Faculty-per-student	*Admin-per-student*	*Admin-per-student*

Table 22. (Continued) School Resource Estimated Coefficients (Persistence), Alternative IV Methodologies*

School Resource Indicators	Random-effects probit (1984–1989)	Random-effects probit (1984–1989), time-constant unobserved het.	Two-step (minimum)	Two-step (maximum)
	(1)	(2)	(3)	(4)
Financial aid spending	0.284***	0.284***	0.369***	0.722***
	(0.028)	(0.028)	(0.046)	(0.074)
	[0.054]	[0.054]	[0.070]	[0.135]
Instrumental variable			*Research*	*Admin-per-student*
Total spending	0.367***	0.366***	0.494***	0.516***
	(0.037)	(0.037)	(0.043)	(0.044)
	[0.069]	[0.069]	[0.091]	[0.095]
Instrumental variable			*Faculty-per-student*	*Admin-per-student*
Number of observations	14546	14546	14546	14546

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.
Minimum and maximum values reported are based on marginal effects.
Shaded regions indicate that no valid instrument could be obtained for the endogenous resource indicator, so an invalid instrument was used in the reported estimates.
Due to low intertemporal variation in school resource indicators, the random-effects probit and Papke and Wooldridge ML estimations incorporating time-constant unobserved heterogeneity include only averages of household income and local labor market unemployment rate as additional explanatory variables.

Standard ML Estimator (minimum)	**Standard ML Estimator (maximum)**	**Papke & Wooldridge ML Estimator (maximum)**
(5)	**(6)**	**(7)**
0.386***	0.851***	0.813**
(0.047)	(0.221)	(0.353)
[0.077]	[0.177]	[0.164]
Instruction	*Admin-per-student*	*Admin-per-student*
	1.035***	1.075***
	(0.212)	(0.378)
	[0.214]	[0.216]
	Admin-per-student	*Admin-per-student*
14546	14546	14546

Table 23. School Resource Marginal Effects at Different Percentiles of the Resource Distribution (Persistence)*

Percentile	Faculty-student ratio (1)	Instruction spending (2)	Research spending (3)	Academic-related spending (4)	Financial aid spending (5)	Total spending (6)
5th	30.622***	0.416***	0.000	0.390***	0.057***	0.299***
	(1.948)	(0.146)	(0.000)	(0.101)	(0.003)	(0.085)
10th	19.297***	0.303	0.001***	0.316**	0.132***	0.250**
	(2.705)	(0.206)	(0.000)	(0.156)	(0.030)	(0.124)
25th	3.168**	0.133	0.085***	0.166	0.240***	0.138
	(1.282)	(0.192)	(0.026)	(0.186)	(0.085)	(0.155)
50th	0.171	0.028	0.428***	0.047	0.324***	0.048
	(0.136)	(0.076)	(0.038)	(0.105)	(0.108)	(0.103)
75th	0.001	0.007	0.043	0.009	0.335***	0.015
	(0.001)	(0.027)	(0.042)	(0.032)	(0.068)	(0.047)
90th	0.000	0.001	0.007	0.001	0.271***	0.004
	(0.000)	(0.007)	(0.011)	(0.006)	(0.022)	(0.018)
95th	0.000	0.000	0.002	0.000	0.218***	0.002
	(0.000)	(0.002)	(0.004)	(0.002)	(0.061)	(0.008)
Instrument	*Research*	*Admin-per-student*	*Financial aid*	*Admin-per-student*	*Admin-per-student*	*Admin-per-student*

*Note: Values in parentheses are standard errors and values in brackets are marginal effects.
**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 24. Summary Statistics (Cost Efficiency), 2006-2011

Variable	Mean	Standard Deviation
Dependent Variable		
Log Total Expenses*	8.94	1.16
Cost Frontier Independent Variables		
Outputs		
Log Full-Time Equivalent (FTE) Undergraduate Students	8.44	1.08
Log FTE Graduate Students	6.94	1.20
Log Federal and State Grants and Contracts Revenue	10.40	3.26
Input Prices		
Log Average Salaries and Wages Plus Fringe Benefits (instruction)*	1.42	0.93
Log Average Salaries and Wages Plus Fringe Benefits (noninstruction)*	0.43	0.69
Quality Indicators		
Barron's Most Competitive Dummy	0.05	0.22
Barron's Very Competitive Dummy	0.07	0.25
Barron's Highly Competitive Dummy	0.21	0.41
Barron's Competitive Dummy	0.49	0.50
Barron's Less Competitive/Noncompetitive Dummy	0.14	0.35
Log SAT Math 75th Percentile	5.25	2.45
Log ACT Composite 75th Percentile	2.68	1.22
2014 Forbes Ranking	181.82	222.79
2015 US News and World Report Ranking	92.63	69.63
US News Ranking*US News Institutional Category	193.99	169.76
Carnegie Classifications		
Doctoral/Research Universities-Extensive	0.18	0.38
Doctoral/Research Universities-Intensive	0.12	0.33
Master's Colleges and Universities-I	0.58	0.49
Master's Colleges and Universities-II	0.12	0.32
Other Controls		
Public Institution Dummy	0.52	0.50
Medical Degree Dummy	0.14	0.34
Hospital Dummy	0.05	0.21

Table 24. (Continued) Summary Statistics (Cost Efficiency), 2006-2011

Variable	Mean	Standard Deviation
Inefficiency Determinants		
Student Characteristics		
% Part-Time Students	26.73	15.17
% Undergraduates Aged 25 and Over	18.09	16.45
% Nonwhite Students	22.45	24.85
% Female Students	58.70	10.18
% Science Students	3.82	8.94
Staff Characteristics		
% Female Instructors	43.77	9.89
% Professors	28.29	10.65
% Nonwhite Staff	13.24	19.45
Cost Shares		
Instruction	46.07	10.67
Research	7.01	10.96

*Capital input price (depreciation expense per FTE staff) was used to normalize cost and input prices to satisfy the price homogeneity condition.

Table 25. One-Step Stochastic Cost Frontier (Stage 1) Estimates*

Dependent Variable: Total Cost	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Full-Time Equivalent (FTE)	-0.281***	0.152***	0.105**	0.138***	0.014	0.031	0.052
Undergraduate Enrollment	(0.067)	(0.050)	(0.048)	(0.049)	(0.790)	(0.050)	(0.049)
FTE Graduate Enrollment	0.454***	0.362***	0.318***	0.312***	0.298	0.302***	0.286***
	(0.070)	(0.046)	(0.045)	(0.045)	(0.834)	(0.046)	(0.046)
FTE Undergraduate Enrollment^2	0.129***	0.068***	0.066***	0.055***	0.094	0.101***	0.097***
	(0.009)	(0.008)	(0.008)	(0.007)	(0.577)	(0.008)	(0.007)
FTE Graduate Enrollment^2	0.028***	0.056***	0.056***	0.052***	0.076	0.077***	0.082***
	(0.011)	(0.007)	(0.007)	(0.007)	(0.533)	(0.008)	(0.008)
Research Revenue	-0.045***	-0.120***	-0.105***	-0.097***	-0.135	-0.129***	-0.134***
	(0.014)	(0.011)	(0.011)	(0.011)	(0.761)	(0.011)	(0.011)
Research Revenue^2	0.004***	0.001	0.000	0.000	0.005	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.035)	(0.001)	(0.001)
Research*Undergraduate Enrollment	-0.003**	0.007***	0.007***	0.008***	0.003	0.001	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.071)	(0.001)	(0.001)
Research*Graduate Enrollment	0.002	0.006***	0.004***	0.003**	0.007	0.008***	0.008***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.072)	(0.002)	(0.002)
Undergraduate*Graduate Enrollment	-0.081***	-0.093***	-0.085***	-0.079***	-0.101	-0.106***	-0.107***
	(0.010)	(0.007)	(0.007)	(0.007)	(0.541)	(0.007)	(0.007)
Labor Price (instructional)	-1.346***	-1.554***	-1.502***	-1.564***	-1.357	-1.414***	-1.373***
	(0.051)	(0.057)	(0.056)	(0.055)	(0.989)	(0.057)	(0.057)
Labor Price (noninstructional)	-2.603***	-1.870***	-1.802***	-1.612***	-2.256**	-2.185***	-2.225***
	(0.101)	(0.097)	(0.104)	(0.094)	(0.998)	(0.095)	(0.096)

(8)	(9)	(10)
0.225***	0.148***	0.192***
(0.050)	(0.049)	(0.050)
0.383***	0.328***	0.351***
(0.046)	(0.045)	(0.046)
0.056***	0.049***	0.050***
(0.008)	(0.008)	(0.007)
0.047***	0.045***	0.045***
(0.008)	(0.007)	(0.007)
-0.118***	-0.082***	-0.092***
(0.011)	(0.011)	(0.011)
0.001	0.000	0.000
(0.001)	(0.001)	(0.001)
0.007***	0.007***	0.007***
(0.001)	(0.001)	(0.001)
0.006***	0.002	0.003**
(0.002)	(0.002)	(0.002)
-0.089***	-0.074***	-0.079***
(0.007)	(0.007)	(0.007)
-1.764***	-1.725***	-1.810***
(0.058)	(0.059)	(0.052)
-1.754***	-1.316***	-1.414***
(0.095)	(0.010)	(0.098)

Table 25. (Continued) One-Step Stochastic Cost Frontier (Stage 1) Estimates*

Dependent Variable: Total Cost	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Barron´s Most Competitive Dummy	0.067	0.135***	0.061**	0.086***	0.089	0.131***	0.085***
	(0.053)	(0.030)	(0.029)	(0.029)	(0.983)	(0.029)	(0.028)
Barron´s Very Competitive Dummy	0.011	0.037	0.014	0.027	-0.001	0.049**	0.021
	(0.039)	(0.022)	(0.021)	(0.022)	(0.972)	(0.021)	(0.022)
Barron´s Highly Competitive Dummy	-0.001	0.029	0.0129	0.018	-0.006	0.032**	0.011
	(0.028)	(0.015)	(0.015)	(0.015)	(0.971)	(0.015)	(0.015)
Barron´s Competitive Dummy	-0.034	-0.014	-0.024**	-0.021	-0.031	-0.014	-0.029**
	(0.023)	(0.012)	(0.012)	(0.012)	(0.950)	(0.013)	(0.012)
Public Institution Dummy	-0.244***	-0.212***	-0.228***	-0.215***	-0.227	-0.251***	-0.237***
	(0.027)	(0.016)	(0.015)	(0.016)	(0.757)	(0.016)	(0.016)
Medical Degree Dummy	0.203***	0.152***	0.142***	0.146***	0.136	0.136***	0.150***
	(0.029)	(0.019)	(0.019)	(0.019)	(0.941)	(0.019)	(0.019)
Hospital Dummy	0.233***	0.185***	0.148***	0.136***	0.256	0.257***	0.259***
	(0.040)	(0.027)	(0.028)	(0.027)	(0.987)	(0.027)	(0.028)
Time	-0.009**	0.003	0.002	-0.010***	-0.011	0.163***	0.047***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.352)	(0.021)	(0.016)

(8)	(9)	(10)
0.134***	0.057	0.130***
(0.030)	(0.032)	(0.031)
0.064***	0.056**	0.069***
(0.022)	(0.023)	(0.022)
0.049***	0.034**	0.048***
(0.015)	(0.016)	(0.015)
0.000	-0.009	-0.001
(0.013)	(0.013)	(0.012)
-0.222***	-0.213***	-0.211***
(0.016)	(0.016)	(0.016)
0.159***	0.127***	0.141***
(0.019)	(0.019)	(0.019)
0.189***	0.079***	0.126***
(0.027)	(0.027)	(0.027)
0.001	0.002	0.001
(0.003)	(0.003)	(0.003)

Table 25. (Continued) One-Step Stochastic Cost Frontier (Stage 1) Estimates*

Dependent Variable: Total Cost	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Doctoral/Research Universities-	0.200***	0.127***	0.109***	0.110***	0.134	0.132***	0.115***
Extensive	(0.051)	(0.028)	(0.028)	(0.028)	(0.943)	(0.028)	(0.028)
Doctoral/Research Universities-	0.139***	0.081***	0.068***	0.066***	0.076	0.070***	0.063***
Intensive	(0.041)	(0.022)	(0.021)	(0.022)	(0.939)	(0.022)	(0.022)
Master Colleges and Universities-I	0.083***	0.074***	0.068***	0.069***	0.061	0.048***	0.048***
	(0.030)	(0.015)	(0.014)	(0.015)	(0.959)	(0.015)	(0.015)
Constant	6.530***	5.224***	5.594***	5.464***	6.306***	5.184***	5.819***
	(0.410)	(0.272)	(0.267)	(0.268)	(0.989)	(0.295)	(0.279)

*Note: Values in parentheses are standard errors.

**Denotes significance at the 5% level and ***denotes significance at the 1% level.

(8)	(9)	(10)
0.132***	0.085***	0.100***
(0.028)	(0.028)	(0.028)
0.075***	0.060***	0.062***
(0.022)	(0.022)	(0.022)
0.062***	0.063***	0.062***
(0.015)	(0.015)	(0.015)
4.878***	5.295***	5.077***
(0.274)	(0.265)	(0.275)

Table 26. One-Step Inefficiency Effects (Stage 2) Estimates*

Dependent Variable: Inefficiency	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Instruction Share of Revenue		0.004		0.038***			
		(0.008)		(0.012)			
Instruction Share of Revenue^2		-0.001***		-0.001***			
		(0.000)		(0.000)			
Research Share of Revenue			0.050***	0.078***			
			(0.004)	(0.004)			
Research Share of Revenue^2			-0.000***	-0.001***			
			(0.000)	(0.000)			
% Part-time Students					-0.003		-0.001***
					(0.011)		(0.001)
% Undergraduates Aged 25 and Over					-0.002		0.000
					(0.041)		(0.001)
% Nonwhite Students					0.000		
					(0.010)		
% Female Students					0.002		
					(0.033)		
% Science Students					-0.003		
					(0.044)		
% Female Instructors						0.004***	0.004***
						(0.001)	(0.001)
% Professors						0.001***	0.001
						(0.000)	(0.001)

(8)	(9)	(10)
-0.083***		0.012
(0.009)		(0.006)
0.000		-0.001***
(0.000)		(0.000)
	0.195***	0.097***
	(0.015)	(0.004)
	-0.002***	-0.001***
	(0.000)	(0.000)
0.003***	-0.011***	0.010***
(0.001)	(0.002)	(0.001)
0.012***	0.017***	0.009***
(0.002)	(0.002)	(0.001)
0.035***	0.060***	0.050***
(0.004)	(0.004)	(0.001)
0.023***	0.024***	0.020***
(0.003)	(0.003)	(0.001)

Table 26. (Continued) One-Step Inefficiency Effects (Stage 2) Estimates*

Dependent Variable: Inefficiency	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
% Nonwhite Staff						0.001**	0.001**
						(0.000)	(0.000)
Time		-0.095***	-0.039**	0.010	0.003	-0.178***	-0.063***
		(0.015)	(0.019)	(0.007)	(0.530)	(0.019)	(0.015)
Constant		0.511***	-1.228***	-2.426***	0.004	0.780***	0.174
		(0.148)	(0.068)	(0.316)	(0.986)	(0.130)	(0.099)
Turning Point: Instruction		2.239	n.a.	14.915	n.a.	n.a.	n.a.
Turning Point: Research		n.a.	86.837	75.187	n.a.	n.a.	n.a.
Mean Cost Inefficiency	1.717	1.245	1.259	1.257	1.076	1.546	1.169
Sigma-squared	0.110***	0.402***	0.322***	0.624***	0.092***	0.088***	0.088***
	(0.004)	(0.020)	(0.028)	(0.022)	(0.007)	(0.002)	(0.002)
Gamma	0.572***	0.868***	0.830***	0.920***	0.025***	0.003**	0.028
	(0.013)	(0.009)	(0.021)	(0.004)	(0.760)	(0.001)	(0.016)
Mu	0.501***						
	(0.028)						
Eta	-0.012						
	(0.010)						
Number of observations	4950	4950	4950	4950	4950	4950	4950
Log-likelihood function	-265.771	-889.923	-922.182	-871.668	-1031.786	-996.878	-986.754
LR test of the one-sided error	1572.260	323.956	259.439	360.466	40.229	110.045	130.293

*Note: Values in parentheses are standard errors.

**Denotes significance at the 5% level and ***denotes significance at the 1% level.

(8)	**(9)**	**(10)**
0.010***	0.011***	0.006***
(0.001)	(0.001)	(0.001)
-0.080***	-0.019**	0.036**
(0.013)	(0.009)	(0.017)
-0.811	-7.383***	-4.834***
(0.456)	(0.610)	(0.216)
n.a.	n.a.	6.061
n.a.	44.158	48.811
1.273	1.327	1.303
0.500***	0.679***	0.615***
(0.036)	(0.049)	(0.021)
0.900***	0.933***	0.926***
(0.009)	(0.006)	(0.004)
4950	4950	4950
-815.799	-806.570	-757.394
472.203	490.662	589.014

Table 27. One-Step Stochastic Cost Frontier (Stage 1) Estimates for Alternative Quality Indicators*

Dependent Variable: Total Cost	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Log SAT Math 75th Percentile			0.231***			
			(0.061)			
Log ACT Composite 75th Percentile				0.252***		
				(0.052)		
Forbes Ranking					-0.000***	
					(0.000)	
US News and World Report Ranking						-0.000**
						(0.000)
US News Ranking*Institutional Category						-0.000***
						(0.000)
Barron's Most Competitive Dummy		0.130***				
		(0.031)				
Barron's Very Competitive Dummy		0.069***				
		(0.022)				
Barron's Highly Competitive Dummy		0.048***				
		(0.015)				
Barron's Competitive Dummy		-0.001				
		(0.012)				

Table 27. (Continued) One-Step Stochastic Cost Frontier (Stage 1) Estimates for Alternative Quality Indicators*

Dependent Variable: Total Cost	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Public Institution Dummy	-0.241***	-0.211***	-0.221***	-0.215***	-0.205***	-0.195***
	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)
Medical Degree Dummy	0.139***	0.141***	0.145***	0.139***	0.144***	0.139***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Hospital Dummy	0.130***	0.126***	0.131***	0.130***	0.133***	0.130***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.026)
Time	0.000	0.001	0.001	0.000	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Doctoral/Research Universities-Extensive	0.139***	0.100***	0.119***	0.114***	0.094***	0.139***
	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Doctoral/Research Universities-Intensive	0.079***	0.062***	0.071***	0.071***	0.067***	0.092***
	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)	(0.024)
Master's Colleges and Universities-I	0.070***	0.062***	0.068***	0.066***	0.061***	0.058***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)
Constant	4.957***	5.077***	3.620***	4.308***	5.078***	5.302***
	(0.273)	(0.275)	(0.452)	(0.310)	(0.273)	(0.273)

*Note: Values in parentheses are standard errors.

**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 28. One-Step Inefficiency Effects (Stage 2) Estimates for Alternative Quality Indicators*

Dependent Variable: Inefficiency	(1)	(2)	(3)	(4)	(5)	(6)
Instruction Share of Revenue	-0.079***	0.012	-0.048***	-0.052***	-0.062***	-0.078***
	(0.011)	(0.006)	(0.009)	(0.011)	(0.015)	(0.018)
Instruction Share of Revenue^2	0.000	-0.001***	-0.000***	-0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Research Share of Revenue	0.132***	0.097***	0.120***	0.121***	0.131***	0.119***
	(0.006)	(0.004)	(0.006)	(0.007)	(0.007)	(0.006)
Research Share of Revenue^2	-0.001***	-0.001***	-0.001***	-0.002***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Part-Time Students	0.011***	0.010***	0.012***	0.010***	0.013***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% Undergraduates Aged 25 and Over	0.009***	0.009***	0.012***	0.014***	0.014***	0.013***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% Female Instructors	0.052***	0.050***	0.051***	0.049***	0.055***	0.053***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
% Professors	0.015***	0.020***	0.022***	0.021***	0.024***	0.025***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
% Nonwhite Staff	0.007***	0.006***	0.012***	0.010***	0.011***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Table 28. (Continued) One-Step Inefficiency Effects (Stage 2) Estimates for Alternative Quality Indicators*

Dependent Variable: Inefficiency	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Time	0.058***	0.036**	0.017	-0.016	-0.028	0.014
	(0.014)	(0.017)	(0.013)	(0.014)	(0.015)	(0.014)
Constant	-4.105***	-4.834***	-4.789***	-4.389***	-4.966***	-4.170***
	(0.188)	(0.216)	(0.203)	(0.189)	(0.165)	(0.180)
Turning Point: Instruction	n.a.	6.061	n.a.	n.a.	n.a.	n.a.
Turning Point: Research	47.859	48.811	49.530	46.551	48.178	45.181
Mean Cost Inefficiency	1.313	1.303	1.303	1.296	1.322	1.313
Sigma-squared	0.836***	0.615***	0.776***	0.771***	0.862***	0.765***
	(0.029)	(0.021)	(0.033)	(0.033)	(0.033)	(0.032)
Gamma	0.945***	0.926***	0.941***	0.939***	0.948***	0.942***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Number of observations	4950	4950	4950	4950	4950	4950
Log-likelihood function	-768.441	-757.394	-756.265	-749.709	-739.167	-724.896
LR test of the one-sided error	593.336	589.014	597.442	602.272	609.954	658.790

*Note: Values in parentheses are standard errors.

**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 29. Hypotheses Tests for Parameters of the Inefficiency Frontier Model*

Null Hypothesis	Critical Value	Test-Statistic	Decision
$\gamma=0$	11.34	589.01	Reject H_o
$\tau_0=0$	6.63	97.2	Reject H_o
$\tau_1=\tau_2=\tau_3=\tau_4=\tau_5=\tau_6=\tau_7=\tau_8=\tau_9=\tau_{10}=0$	23.21	547.65	Reject H_o
$\gamma=\tau_0=\tau_1=\tau_2=\tau_3=\tau_4=\tau_5=\tau_6=\tau_7=\tau_8=\tau_9=\tau_{10}=0$	24.72	589	Reject H_o

*The likelihood ratio statistic, $\lambda= -2\{\log[\text{Likelihood}(H_o)] - \log[\text{Likelihood}(H_1)]\}$, has approximately a chi-square distribution with degrees of freedom equal to the number of parameters assumed to be zero in the null hypothesis H_o, provided H_o is true.

Table 30. One-Step Stochastic Cost Frontier (Stage 1) Estimates for Alternative Cost Functions*

Dependent Variable: Total Cost	Translog	Cobb-Douglas	Quadratic
Full-Time Equivalent (FTE) Undergraduate	0.192***	0.611***	0.812***
Enrollment	(0.050)	(0.011)	(0.055)
FTE Graduate Enrollment	0.351***	0.118***	0.164***
	(0.046)	(0.008)	(0.054)
FTE Undergraduate Enrollment^2	0.050***		-0.013
	(0.007)		(0.010)
FTE Graduate Enrollment^2	0.045***		0.086***
	(0.007)		(0.009)
Research Revenue	-0.092***	0.017***	-0.322***
	(0.011)	(0.003)	(0.010)
Research Revenue^2	0.000		0.004***
	(0.001)		(0.001)
Research*Undergraduate Enrollment	0.007***		0.032***
	(0.001)		(0.002)
Research*Graduate Enrollment	0.003**		0.011***
	(0.002)		(0.001)
Undergraduate*Graduate Enrollment	-0.079***		-0.093***
	(0.007)		(0.008)
Labor Price (instructional)	-1.810***	0.910***	0.741***
	(0.052)	(0.013)	(0.030)
Labor Price (noninstructional)	-1.414***	0.016	-0.030
	(0.098)	(0.015)	(0.028)
Barron’s Most Competitive Dummy	0.130***	0.294***	0.165***
	(0.031)	(0.036)	(0.038)
Barron’s Very Competitive Dummy	0.069***	0.119***	0.064**
	(0.022)	(0.027)	(0.029)
Barron’s Highly Competitive Dummy	0.048***	0.088***	0.056***
	(0.015)	(0.018)	(0.020)
Barron’s Competitive Dummy	-0.001	0.001	-0.008
	(0.012)	(0.015)	(0.016)

Table 30. (Continued) One-Step Stochastic Cost Frontier (Stage 1) Estimates for Alternative Cost Functions*

Dependent Variable: Total Cost	Translog	Cobb-Douglas	Quadratic
Public Institution Dummy	-0.211***	-0.253***	-0.301***
	(0.016)	(0.016)	(0.019)
Medical Degree Dummy	0.141***	0.233***	0.184***
	(0.019)	(0.023)	(0.023)
Hospital Dummy	0.126***	0.091**	0.134***
	(0.027)	(0.036)	(0.032)
Time	0.001	0.010***	-0.014***
	(0.003)	(0.003)	(0.003)
Doctoral/Research Universities-Extensive	0.100***	0.098***	0.134***
	(0.028)	(0.031)	(0.034)
Doctoral/Research Universities-Intensive	0.062***	0.060**	0.122***
	(0.022)	(0.025)	(0.027)
Master's Colleges and Universities-I	0.062***	0.043**	0.082***
	(0.015)	(0.017)	(0.019)
Constant	5.077***	0.881***	0.677**
	(0.275)	(0.080)	(0.308)

*Note: Values in parentheses are standard errors.

**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 31. One-Step Inefficiency Effects (Stage 2) Estimates for Alternative Cost Functions*

Dependent Variable: Total Cost	Translog	Cobb-Douglas	Quadratic
Instruction Share of Revenue	0.012	-0.120***	-0.075***
	(0.006)	(0.025)	(0.025)
Instruction Share of Revenue^2	-0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)
Research Share of Revenue	0.097***	-0.056***	-0.116***
	(0.004)	(0.008)	(0.008)
Research Share of Revenue^2	-0.001***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)
% Part-Time Students	0.010***	0.007***	0.000
	(0.001)	(0.002)	(0.001)
% Undergraduates Aged 25 and Over	0.009***	0.036***	0.014***
	(0.001)	(0.003)	(0.002)
% Female Instructors	0.050***	0.022***	0.010***
	(0.001)	(0.003)	(0.002)
% Professors	0.020***	0.015***	0.002
	(0.001)	(0.002)	(0.001)
% Nonwhite Staff	0.006***	0.039***	0.027***
	(0.001)	(0.003)	(0.002)
Time	0.036**	-0.881***	-0.648***
	(0.017)	(0.066)	(0.024)
Constant	-4.834***	-2.181***	-0.926
	(0.216)	(0.559)	(0.537)
Turning Point: Instruction	-6.061	n.a.	n.a.
Turning Point: Research	48.811	24.472	31.842
Mean Cost Inefficiency	1.303	14.997	1.982
Sigma-squared	0.615***	2.041***	1.123***
	(0.021)	(0.169)	(0.056)
Gamma	0.926***	0.980***	0.964***
	(0.004)	(0.002)	(0.002)
Number of observations	4950	4950	4950
Log-likelihood function	-757.394	-2251.294	-1901.605
LR test of the one-sided error	589.014	1817.500	898.131

*Note: Values in parentheses are standard errors.

**Denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 32. Pairwise Pearson Correlation Coefficient of Predicted Cost Inefficiencies

Correlation Coefficient	Exponent Time	No Quality	Barron's	Log (SAT)	Log (ACT)	Forbes	US News	Cobb-Douglas	Quadratic	Total Students
Exponent Time	1									
No Quality	0.18	1								
Barron's	0.21	0.99	1							
Log (SAT)	0.19	1.00	1.00	1						
Log (ACT)	0.20	1.00	1.00	1.00	1					
Forbes	0.14	0.99	0.98	0.99	0.98	1				
US News	0.17	1.00	0.99	1.00	0.99	1.00	1			
Cobb-Douglas	0.00	0.84	0.78	0.81	0.79	0.90	0.86	1		
Quadratic	0.05	0.73	0.68	0.71	0.69	0.77	0.74	0.83	1	
Total Students	0.16	1.00	0.99	1.00	0.99	0.99	0.99	0.83	0.72	1

Table 33. Pairwise Spearman Rank Correlation Coefficient of Predicted Cost Inefficiencies

Correlation Coefficient	Exponent Time	No Quality	Barron's	Log (SAT)	Log (ACT)	Forbes	US News	Cobb-Douglas	Quadratic	Total Students
Exponent Time	1									
No Quality	0.60	1								
Barron's	0.58	0.99	1							
Log (SAT)	0.60	0.99	0.99	1						
Log (ACT)	0.59	0.99	0.99	1.00	1					
Forbes	0.59	0.99	0.99	0.99	0.99	1				
US News	0.59	0.99	0.99	0.99	0.99	0.99	1			
Cobb-Douglas	0.49	0.60	0.60	0.62	0.62	0.62	0.62	1		
Quadratic	0.49	0.53	0.53	0.55	0.54	0.54	0.54	0.88	1	
Total Students	0.59	0.98	0.98	0.98	0.98	0.98	0.97	0.61	0.52	1

APPENDIX B. ONE-STEP VERSUS TWO-STEP METHODOLOGIES

In this section, I highlight the importance of using the one-step, as opposed to the two-step, methodology in the estimation of cost frontiers and the prediction of cost inefficiencies. The simultaneous estimation of the cost frontier and inefficiency effects equation is commonly referred to in the literature as the one-step methodology, while separate estimation of the cost frontier (stage 1) and the inefficiency effects equation (stage 2), commonly using OLS, is known as the two-step procedure. Wang and Schmidt (2002) showed using Monte Carlo evidence that, among others, a two-step procedure that ignores environmental variables in the estimation of a first-stage cost frontier leads to underdispersed predicted cost efficiencies and downward-biased estimated coefficients for the environmental variables in the second-stage estimation. The lower standard deviation arises because the role of the environmental variables, which cause greater variability in the inefficiency effects, is ignored in the prediction of the cost inefficiencies. These Monte Carlo results were also found to be true using the data in this study.

Table 34 reports the mean, standard deviation, and minimum and maximum values of the predicted cost inefficiencies for the one-step and two-step estimations of preferred cost frontier specifications. Similar to the predictions of Wang and Schmidt (2002) for positively related environmental variables and predicted cost inefficiencies, the standard deviations of predicted cost inefficiencies are underdispersed or are lower in the simpler models that specify the inefficiency effects as exponential or linear functions of time only. These simpler models have statistically significant lower standard deviations for predicted cost inefficiencies compared to those obtained from all the preferred specifications and alternative functional forms.

The estimated coefficients for the inefficiency determinants in the preferred one-step specification (column 1) and two variants of the two-step specifications (columns 2 and 3) are reported in Table 35. Both two-step specifications estimate the cost frontier that models inefficiency effects as either a linear or exponential function of time only in stage 1 and utilizes OLS in stage 2 to regress the predicted cost inefficiencies obtained in stage 1 against student, staff, and cost share characteristics. The estimated coefficients for all student and staff characteristics in both variants of the two-step specifications either decrease significantly or become statistically insignificant. These results could be explained by the inability of the two-step specifications to recognize the positive, statistically significant relationship of the student and staff characteristics with the inefficiency effects obtained in the one-step specification, which then leads to underdispersion of the predicted cost inefficiencies and consequently decreased explanatory power of the inefficiency determinants. The poor specification of the inefficiency effects equation is also evident in the second step OLS R-squared value of less than 0.1.

Table 34. Summary Statistics of Predicted Cost Inefficiencies from Alternative Models

Specification		**No. of Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Inefficiency Effects as Function of Time	Exponential	4950	1.717	**0.381**	1.02	4.75
	Linear	4950	1.238	**1.166**	1.04	58.30
Preferred Specifications Using Alternative Quality Indicators	Barron's	4950	1.303	**1.211**	1.03	50.40
	Log SAT	4950	1.303	**1.365**	1.03	59.30
	Log ACT	4950	1.296	**1.294**	1.03	55.00
	Forbes	4950	1.323	**1.914**	1.03	90.60
	US News	4950	1.313	**1.575**	1.03	71.60
	No Quality	4950	1.313	**1.504**	1.03	67.60
Alternative Cost Functions	Cobb-Douglas	4950	14.985	**642.136**	1.03	32000.00
	Quadratic	4950	1.982	**5.055**	1.00	214.00

Table 35. One-Step versus Two-Step Estimated Coefficients of Inefficiency Determinants*

Inefficiency Determinants	One-Step: Main (Quality:	Two-Step	
		Exponential Time	Linear Time
	(1)	(2)	(3)
Instruction Share of Revenue	0.01218***	-0.01629***	-0.00564
	(0.00633)	(0.00488)	(0.01554)
Instruction Share of Revenue^2	-0.00101***	0.00011**	0.00002
	(0.00009)	(0.00005)	(0.00017)
Research Share of Revenue	0.09732***	-0.00562***	0.00058
	(0.00357)	(0.00128)	(0.00406)
Research Share of Revenue^2	-0.00100***	0.00017***	0.00004
	(0.00005)	(0.00003)	(0.00010)
% Part-Time Students	0.01043***	-0.00094**	0.00061
	(0.00108)	(0.00046)	(0.00146)
% Undergraduates Aged 25 and Over	0.00893***	0.00031	0.00143
	(0.00102)	(0.00047)	(0.00149)
% Female Instructors	0.05029***	0.00657***	0.00147
	(0.00123)	(0.00065)	(0.00207)
% Professors	0.01983***	0.00277***	-0.00172
	(0.00105)	(0.00056)	(0.00179)
% Nonwhite Staff	0.00570***	0.00063	0.00099
	(0.00056)	(0.00038)	(0.00122)
Time	0.03562**		-0.62749***
	(0.01724)		(0.03989)
Constant	-4.83000	1.85975***	1.41940***
	(0.21600)	(0.11896)	(0.37871)
No. of observations	4950	4950	4950
R-squared		0.0816	0.006

*Note: Values in parentheses are standard errors.

**Denotes significance at the 5% level and ***denotes significance at the 1% level.

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