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Higher education surveys from United States' National Center for Education Statistics

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Abstract: In this article, we analysed the use of surveys conducted by the United States' National Center for Education Statistics (NCES) related to postsecondary education in studies published in 2015. We discuss topics studied, methods used and limitations reported. Based on the review of the 27 published articles in 2015, we found that the most commonly used NCES postsecondary surveys are ELS:2002 and IPEDS, followed by BPS:04/09, NPSAS, NELS:1988, B&B:1993/1997/2003 and HSLS:2009. The issues studied in the articles reviewed include college access and choice, student outcomes and higher education finances. In addition, our analysis indicates that these articles applied appropriate and advanced analytical methods and the majority of them took into consideration the complex sampling designs and data structures of these NCES surveys. We concluded with a series of recommendations for both users and leaders developing these surveys in order to maximise their utility. These recommendations, if adopted, will undoubtedly result in more use of NCES data for research.

Keywords: higher education; large-scale secondary data; NCES.

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1 Introduction

Despite the availability of secondary data collected by government agencies in the USA, researchers, especially international researchers, may not be aware of or use them for their research. The main purpose of this theoretical article is to illustrate the use of surveys conducted by the United States' National Center for Education Statistics (NCES) related to postsecondary education through an analysis of studies published in 2015 using these surveys along with recommendations for researchers and policymakers on the use and development of national databases.

The US federal government has collected statistics on the condition and progress of American education since 1870 focusing on enrolment, attendance, teacher salaries, high school graduates, school expenditures and number of faculty and degrees conferred in higher education. Gradually, the complexity of the surveys increased to include private institutions, budgets breakdown and demographic characteristics of students as well as degrees conferred by fields, level and type of institutions at the postsecondary level (AllGov, 2016). In 2002, President George W. Bush established the Institute of Education Sciences (IES) as the leading source for rigorous independent education research, evaluation and statistics used by policymakers, education leaders, teachers and researchers to ground educational practice and policy. The work of IES encompasses six major areas:

a Collection and analysis of data on the state of American education including adult and literacy education, international assessments and the national assessment of educational progress, which focuses on students' knowledge and skills in various subject areas.

b Implementation of longitudinal and cross-sectional surveys and funding of research for the improvement of educational systems.

c Funding for testing educational approaches in areas such as instruction, student behaviour, teacher learning and school and system organisation.

d Implementation of large-scale evaluations of federal education programs and policies in areas such as teacher preparation, leader evaluation systems, school improvement and school choice programs.

e Provision of resources to increase use of data in education research and decision making.

f Training and development in advanced statistics using large datasets such as those collected by IES (2016a).

In addition, IES hosts four national centres including The National Center for Education Research (NCER), The National Center for Education Evaluation and Regional Assistance (NCEE), The National Center for Special Education Research (NCSER) and the NCES (IES, 2016b).

This paper focuses on the use of postsecondary surveys developed by NCES, which is the primary educational statistics federal entity in the USA under the congressional mandate to collect, analyse and disseminate reports about the state of education in the nation (AllGov, 2016). NCES is also charged with assisting education agencies in relation to their statistical programs and reporting on national educational outcomes to international assessments and foreign countries. NCES also administers the National Assessments of Adult Literacy (NAAL) and the Nation's Report Card focusing on the continuing assessment of school-aged children proficiency in mathematics, sciences, economics, reading, writing, arts, civics, geography, US history, technology and engineering literacy (IES, 2016b). NCES data are publicly available via a web-based statistical tool (http://nces.ed.gov/datalab/quickstats/default.aspx), whereas restrictive raw data is available for qualified researchers who are granted a license (https://nces.ed.gov/pubsearch/licenses.asp).

This study aims to understand how the data from these NCES postsecondary surveys are used in research. To achieve this, we first identified published articles using NCES postsecondary surveys. Then, we used content analysis to reveal how NCES surveys were used in higher education research. Content analysis is a research method for analysing written, verbal or visual documents, which allows researchers to describe and quantify meanings of these documents systematically and objectively. Content analysis allows researchers to identify critical processes and summarise concepts or categories describing the phenomenon (Elo and Kyngäs, 2008). To examine how NCES surveys were used, we followed Elo and Kyngäs (2008)'s content analysis steps: preparation, organising and reporting. In the preparation stage, we first selected the unit of analysis. Based on our research question, the unit of analysis of this study are the NCES postsecondary datasets used in the selected articles. In the organising stage, we make sense of the articles by open coding and categorising. In the reporting stage, included in this article, we summarised five categories that were commonly mentioned in these articles based on the open coding:

a The survey design and methodology of the NCES postsecondary datasets that are widely used.

b Issues and research questions that can be addressing using these NCES datasets.

c Analytical methods employed to analyse these NCES datasets.

d Data conditioning (e.g. weights and missing data handling) of these articles.

e How data limitation were addressed in these articles. In doing so, we discuss practical ways to use NCES postsecondary datasets.

2 Studies using NCES postsecondary surveys published in 2015

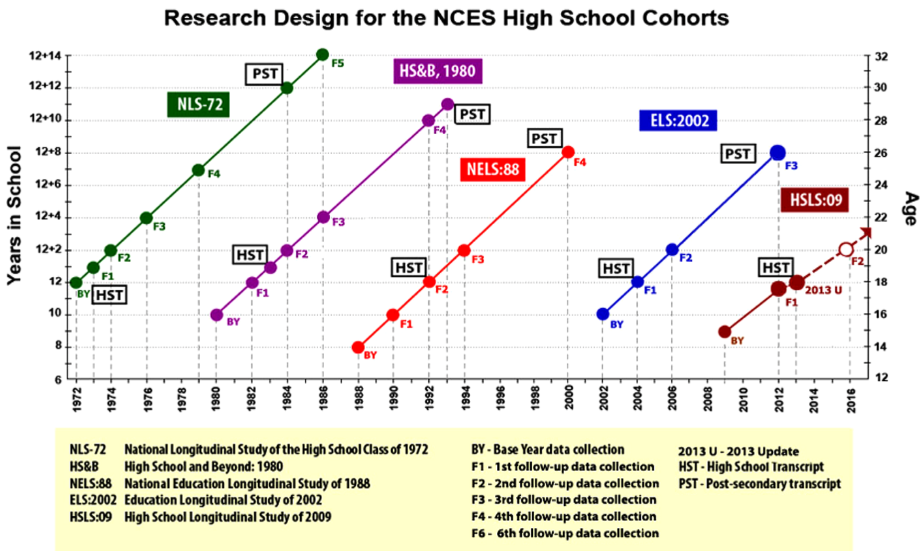
We selected an initial sample of peer reviewed articles using NCES surveys published in 2015 using the bibliography search tool (http://nces.ed.gov/bibliography/) from NCES, which yield a total of 2035 publications. However, many of these publications were duplicated, not empirical, published in non-peer-reviewed journals, focused on school-aged populations or mentioned NCES postsecondary surveys but do not necessarily used them in the analysis. Therefore, we narrowed this sample to articles in journals recognised in Scopus, a comprehensive and reputable database of peer-reviewed articles worldwide and that used postsecondary surveys in the analysis while focusing on postsecondary students. At the end of this screening, we had a sample of 17 articles. In addition, we searched articles published in 2015 in six top higher education journals according to Bray and Major (2011), who examined the status of higher e ducation journals through a faculty survey across the US. These six journals are *The Journal of Higher Education, Review of Higher Education, Research in Higher Education, Journal of College Student Development, Higher Education: Handbook of Theory and Research* and *Higher Education.* We found 10 articles using NCES datasets in these journals, resulting in a total number of 27 articles to be included in this analysis.

We present the results of the analysis based on the five categories used in the coding mentioned above. Table 1 presents a summary of the 27 articles reviewed in relation to these categories.

2.1 NCES datasets used

The surveys used in this sample of articles come from two groups of NCES programs: surveys conducted by the High School Longitudinal Studies Program and the NCES postsecondary surveys. The first group draw initial samples from eighth graders or high school students and then follow them during their transition to postsecondary education. Figure 1 describes the temporal evolutions and components of these surveys. The second group of surveys include students enrolled in postsecondary education (NCES, 2016a, 2016b). In the paragraphs below, we offer a brief description of the NCES surveys used in these studies.

Figure 1 Research Design for the NCES High School Cohorts by *The Secondary School Longitudinal Study*, 2016, Washington, DC: US Department of Education, National Center for Education Statistics. Retrieved from: http://nces.ed.gov/surveys/slsp/researchDesign.asp. Reprinted with permission (see online version for colours)



The most commonly used survey in the sample of articles analysed was the Education Longitudinal Study of 2002 (ELS:2002), used by nine of the 27 articles. This longitudinal survey monitors the transitions of young people as they progress from secondary schooling to subsequent education and work roles. Issues that can be studied through ELS:2002 include the identification of school attributes associated with achievement, the influence of parent and community involvement on students' development, the dynamics of dropping out of school, the transition of different groups from high schools to postsecondary institutions, and the labour market outcomes based on race, gender and socioeconomic status. The base year for data collection was in 2002 and included a two-stage sampling of 750 schools and 17,000 sophomore students as well as students' parents, teachers, librarians, and principals. During the first follow-up in 2004, the same students that were still enrolled were surveyed and tested in mathematics. High school transcripts were also collected. At this point the sample was freshened in order to obtain a representative sample of seniors of the 2004 national class. Then, these students were followed in 2004, 2006 and 2013. The last follow-up focused on students' transition to the workforce and higher education as well as other variables such as community involvement, marital status, and parenthood. High school transcripts and administrative records were also collected in 2006 and 2013 (NCES, 2016c).

Table 1 List of articles published in 2015 using NCES large-scale secondary data to answer questions related to higher education in the USA

Database used	*Topic categories*	*Research questions*	*Methods*	*Conclusion*	*Data limitations*	*Article reference*
B&B:93/97/03	Student outcomes	Is there gender earning gap of college graduates in STEM fields?	Path analysis, sampling weights, listwise deletion	There is gender wage gap within the first ten years of employment		Xu (2015)
BPS:2004–2009	Higher education finance	What are the effects of loans on community college student persistence?	Propensity score matching, sampling weights	Borrowing is positively related to within-year persistence, but it is negatively related to 6-year persistence	Unable to measure the amount of the financial aid, unable to control all factors	McKinney and Burridge (2015)
BPS:2004–2009	Higher education finance	What are the FAFSA filing behaviour among first-year college students?	Logistic regression, sampling weights	Later FAFSA filers receive less total grant aid compared to students who filed earlier	Unable to control all factors	McKinney and Novak (2015)
BPS:2004–2009 IPEDS:2003–2004	College access and choice	Does college student-peer ability match relate to educational aspirations?	Logit models, propensity score matching, sampling weights, listwise deletion	Students who have low SAT and are attending less selective colleges are more likely to decrease in future educational aspirations		Jagešić (2015)
ELS:2002	College access and choice	What factors relate to college undermatch?	Multilevel analysis, sampling weights, missing imputation (chained-equation imputation)	Background, attitudes and high school have significant influence on college undermatch	Nonresponse bias	Belasco and Trivette (2015)
ELS:2002	Student outcomes	How teachers' perceptions influence performance of immigrant and language-minority students?	Multivariate analysis, sampling weights, multiple imputations	Language-minority students are more likely to be negatively perceived		Blanchard and Muller (2015)
ELS:2002	College access and choice	The effect of advanced math course taking on math achievement and college enrolment	Propensity score matching, sampling weights, multiple imputations	Advanced math course taking have positive impacts on math achievement and college enrolment	Data is outdated. Results may only generalisable to high school students cohort 2002	Byun et al. (2015)

Table 1 List of articles published in 2015 using NCES large-scale secondary data to answer questions related to higher education in the USA (continued)

Database used	*Topic categories*	*Research questions*	*Methods*	*Conclusion*	*Data limitations*	*Article reference*
ELS:2002	Student outcomes	What is the impact of SES across educational stages?	Sequential logit modelling, multilevel analysis	Disadvantaged students have substantially lower college enrolment and completion rates compared to their high-SES counterparts		Giani (2015)
ELS:2002	College access and choice	Is taking computer science courses at high school related to students' STEM major choices?	Logistic regression analyses, sampling weights, maximum likelihood (ml)	Students who took more computer science class in high school are more likely to choose STEM majors in both 4- and 2-year colleges		Lee (2015)
ELS:2002	College access and choice	Is racial differences in preferences for staying near family related to college attendance gap?	Ordered logit model, ordinary least-squares models, linear probability models, sampling weights, multiple imputation, multiple imputation with deletion method, listwise deletion	Compared to white students, Hispanic students are more likely to stay at home during college		Ovink and Kalogrides (2015)
ELS:2002	Student outcomes	What factors predict SAT preparation and higher SAT scores?	Multinomial logistic regression, generalised least squares regression	Students who have more cultural capital are more likely to participate in SAT preparation		Park and Becks (2015)
ELS:2002	Student outcomes	What high school factors relate to Hispanic students' high school graduation?	Multilevel analysis, listwise deletion	School safety and same-race friendships is positively related to high school graduation	Unable to measure the degree or quality of the variable	Reed (2015)
ELS:2002	College access and choice	How different ways of estimating college undermatch can produce differential findings?	Logistic regression, sampling weights, multiple imputations	Various ways of estimating college undermatch can produce differential results		Rodriguez (2015)
HSLS:2009	College access and choice	The impact of close friends who are college bound on students' college readiness	Propensity score analysis, missing imputation (STATA 'ice')	Having a college-bound friend is positively related to college readiness generally	Use observational data to infer causal effects	Alvarado and An (2015)

Table 1 List of articles published in 2015 using NCES large-scale secondary data to answer questions related to higher education in the USA (continued)

Database used	*Topic categories*	*Research questions*	*Methods*	*Conclusion*	*Data limitations*	*Article reference*
IPEDS and California community college data mart	Student outcomes	What are the student outcomes of the Hispanic serving institutions (HSIs) in California?	Descriptive statistics, listwise deletion	Most HSIs have lower college completion rates than non- HSIs	Nonresponse bias	Contreras and Contreras (2015)
IPEDS and higher education general information survey	Student outcomes	Do institutional characteristics relate to degree production in humanities?	Fixed-effects, random-effects, fixed-effects vector decomposition	More financial resources are related to humanities degree production overtime		Hearn and Belasco (2015)
IPEDS:2000–2001 through 2012–2013	Higher education finance	What are the effects of sticker-price changes on net tuition revenue?	Fixed effects	In the recession, sticker-price fell is related to net tuition revenue increased		Altringer and Summer (2015)
IPEDS:2002	Student outcomes	Do campus educational contexts and civic participation predict campus action?	Logit regression model, listwise deletion	Campus curricular offerings was associated with campus action	Small sample size	Barnhardt (2015)
IPEDS:1987–2006	Student outcomes	Do state higher education governance structures influence nonresident tuition rates?	Time-series cross-sectional (TSCS), dynamic fixed-effect panel (DFEP) modelling	Nonresident tuition has increased faster in states with low nonresident tuition	Unable to measure the academic performance of participants	Titus et al. (2015)
IPEDS:1990–2006 NSF:WebCASPAR council for aid to education	Student outcomes	What institutional factors predict doctoral completion by international students?	OLS regression analysis, fixed effects, listwise deletion	The number of international students who earned doctoral degree has increased for both public and private universities in the last decade		Taylor and Cantwell (2015)
IPEDS:2002–2003 to 2012–2013	Student outcomes	Do state appropriations decline relate to nonresident freshman enrolment?	Fixed effects panel models, multiple imputations, listwise deletion	Declines of state appropriations positively relate to nonresident freshman enrolment	Unable to control all factors that relate to the dependent variable	Jaquette and Curs (2015)

Table 1 List of articles published in 2015 using NCES large-scale secondary data to answer questions related to higher education in the USA (continued)

Database used	*Topic categories*	*Research questions*	*Methods*	*Conclusion*	*Data limitations*	*Article reference*
NELS:1988	College access and choice	Is there rural-nonrural differences in college attendance?	Multinomial logit models, sampling weights, missing imputation	Rural students are less likely to attend selective institutions compared to their nonrural peers	Data is outdated	Byun et al. (2015)
NELS:1988	Student outcomes	Are the expected incomes different between college students and their peers in employment?	Ordinary least-squares models, fixed effects regression model, sampling weights, listwise deletion	College students make better predictions of their future income than their peers in the labour force	Use predicting data to infer unobserved	Jerrim and Vignoles (2015)
NLS:1972, ELS:2002	College access and choice	The relation between high school GPA and college attendance	Multinomial logit models, sampling weights, missing imputation	High school GPA became more predictive of college enrolment over time	Measures of constructs were not standardised over time	Archibald et al. (2015)
NPSAS:2008	College access and choice	Is student characteristic related to online course enrolment for STEM majors at community college?	Logistic regression, sampling weights, listwise deletion	Race and gender are more important predictors of online enrolment than other characteristics for community college students	Unable to control all factors that relate to the dependent variable	Wladis et al. (2015a)
NPSAS:2000, 2004, 2008 and 2012 current population survey (CPS)	College access and choice, higher education finance	What is the effect of in-state resident tuition (IRT) policy on undocumented student enrolment?	Difference-in-differences, sampling weights	IRT policies have a positive effect on undocumented immigrants' college enrolment	Using a proxy to identify the unobserved variable	Darolia and Potochnick (2015)
NPSAS:2008	Student outcomes	Is gender, race, citizenship and English-as-second-language (ESL) related to online course enrolment?	Logistic regression models, sampling weights, listwise deletion	Nontraditional student characteristics are more likely to predict enrolment in online courses		Wladis et al. (2015b)

Note: B&B, baccalaureate and beyond; BPS, beginning postsecondary survey; ELS, educational longitudinal study; IPEDS, integrated postsecondary education data system; HSLS, high school longitudinal study; NELS, national education longitudinal study; NLS, national longitudinal study; NPSAS, national postsecondary student aid survey

The next most used survey was the Integrated Postsecondary Education Data System (IPEDS), used by four articles. Established as a core and comprehensive postsecondary education data collection program, IPEDS is a system of surveys designed to collect institution-level data from all primary providers of postsecondary education. Postsecondary institutions that received federal funding are required to report their data to this program, therefore, the data includes the vast majorities of institutions in the nation. IPEDS has surveyed institutions in 12 areas, resulting in three reports every year since 1986. Normally, in the fall, the report includes data on institutional characteristics, completions, and enrolment. The winter report includes student financial aid, graduation rates, admissions, and outcome measures. Finally, the spring report consists of fall enrolment, finance, human resources, and academic libraries (NCES, 2016g).

Two of the articles in the sample used the National Postsecondary Student Aid Study (NPSAS), which is a cross-sectional survey focused on the finances of students and their families related to covering the costs of postsecondary education. It collects student-level institutional records, data on financial aid provided by state or institutions as well as students' demographics, family circumstances, education outcomes and work experiences of community college students as well as undergraduate and graduate students attending public and private institutions. This wealth of information is particularly useful for studying the impact of financial aid policies. Data for NPSAS were collected for the first time in 1986–1987 with 40,000 students, and then in 1989–1990 (70,200 students in 1,130 institutions), 1992–1993 (79,269 students in 1,079 institutions), 1995–1996 (63,616 students in 973 institutions), 1999–2000 (59,300 students in 1,000 institutions), 2003–2004 (90,750 students in 1,360 institutions), 2007–2008 (137,800 students in 1,730 institutions) and 2011–2012 (128,120 students in 1,480 institutions). Data collection for the 2015–2016 academic year began in the spring of 2016 (NCES, 2016h).

National postsecondary student aid study data provide the base-year sample for two other surveys, the beginning postsecondary students (BPS) longitudinal study and the baccalaureate and beyond (B&B) longitudinal study. Two of the studies in this analysis used BPS and one study used B&B. Each cycle of BPS follows a cohort of students who are enrolled in postsecondary education for the first time. BPS collects data on persistence and completion, transition to employment, demographic characteristics, and changes over time in their goals, marital status, income, and debt (NCES, 2016a). BPS also tracks students' transition through postsecondary education to explore what percentage of students complete various programs, why students drop out, and how financial aid influences students' persistence and graduation. There are four base years: NPSAS:90, NPSAS:96, NPSAS:04 and NPSAS:12. Then, BPS has followed up each of these cohort, three and six years after these base years. In particular, in the first BPS study, about 10,600 students were identified in NPSAS:90 as being first time beginning postsecondary students during the 1989–1990 academic year. These students were followed up in 1992 (BPS:90/92) and in 1994 (BPS:90/94). A second cohort of first-time college students was identified in NPSAS:96 with around 12,000 students, who were followed up in 1998 (BPS:96/98) and in 2001 (BPS:96/2001). BPS:04/09, followed up in 2006 and 2009, contains information of about 16,700 students. The most recent cohort, BPS:12/17, is based on NPSAS:12 with 37,170 students followed up in 2014, and will be followed up again in 2017 (NCES, 2016i).

Baccalaureate and beyond, the other spin off survey out of NPSAS, surveys students who have completed a bachelor's degree to collect information about their work experiences. It has a special emphasis on the experiences of new school teachers. As such, B&B surveys are geared not only to collect extensive information on bachelor's degree recipients' undergraduate experience, demographic background, students' expectations regarding graduate studies and participation in community service, but also to address several issues related to teaching, including teacher preparation, entry into and persistence in the profession and teacher career paths. B&B surveys students during their senior year of undergraduate studies to measure students' undergraduate education satisfaction as well as their employment expectations. During the later follow-ups, students respond to questions about their entry to the workforce and further education. Respondents who indicated in previous surveys interest in a teaching career are asked additional questions about their teaching pathways. NPSAS provided the base sample of students obtaining a bachelor's degree for B&B in the years 1993, 2000, 2008 and 2016. The first B&B study includes about 11,000 students who completed their degree in 1992–1993. These students were followed up in 1994, 1997 and 2003. The second cohort is based on NPSAS:2000 with approximately 10,000 students who were followed up a year later. The third B&B cohort of about 19,000 students was drawn from NPSAS:08 and was followed up 1 year after graduation in 2009, in 2012–2013, and for a third and final time in 2018 (4 and 10 years after graduation, respectively) (NCES, 2016j).

Two studies used the National Educational Longitudinal Study of 1988 (NELS: 88). NELS:88 was designed to understand the experiences of high school students in the 1990s but with a pre-survey in eighth grade on their academic achievement and status, which enabled the study to look at early dropouts. The base sample included a clustered, stratified national sample of 25,000 students in 1,052 public schools. The cohort of students initially surveyed in 1988 was followed up in 1990, 1992, 1994 and 2000 and included new cross-sectional samples in each of these follow-ups. Transcripts were collected for high schools in 1992 and 1993 and for postsecondary education in 2000 and 2001. The base year survey included cognitive tests in math, science, reading, and history, as well as a range of topics related to school, work, and home experiences; educational resources and support; the role in education of parents and peers; neighbourhood characteristics; educational and occupational aspirations; and other student perceptions. It also reported on other topics such as smoking, alcohol and drug use, and extracurricular activities. To further enrich the data, the study surveyed students' teachers, parents and school administrators (NCES, 2016e).

Finally, one study used the High School Longitudinal Study of 2009 (HSLS:09). This study surveyed a base cohort of about 24,000 ninth graders in 944 high schools during the academic year of 2009–2010 with three main objectives:

a To follow students' trajectories from the beginning of high school into postsecondary education, the workforce and beyond.

b To determine majors and careers choice.

c To determine how students choose science, technology, engineering and math (STEM) courses, majors and careers.

During the base year, students were given an assessment in mathematics and a survey inquiring about their demographics, educational experiences and expectations, and career goals including aspirations in STEM fields. Administrators, math and science teachers, school counsellors, and parents also completed complementary surveys. Administrative records were also collected. The first follow-up was conducted in 2012 (when the majority of the sample was in 11th grade) with essentially the same data from students as in the base year. The second follow-up in 2013 focused on the samples' postsecondary plans and choices including college financial aid as well as entrance to the workforce. In 2013, transcripts were added as well as data from standardised tests (i.e., ACT and SAT), the free application for federal student aid, and general educational development records. The third follow-up took place in 2016 and there are plans to follow this cohort in 2025–2026 when they are about 30 years old (NCES, 2016d).

In addition, six articles used multiple datasets. In particular, Archibald et al. (2015) used both the NLS of the High School Class of 1972 (NLS:72) and ELS:2002 to look at the relation between high school performance and college attendance in the past two decades. NLS:72 is regarded as the seminal survey of longitudinal studies designed and conducted by NCES. In fact, up to 1993, it was the richest archive ever assembled on a single generation of Americans. NLS:72 is widely considered as the benchmark against which the progress and achievements of subsequent cohorts are measured. It describes the transition of 1972 high school graduates to postsecondary education and to the workplace. NLS:72 included a two-stage national representative sample. In the first stage, 1,061 high schools were surveyed; and in the second stage, 19,001 high school seniors enrolled in these high schools in the spring of 1972 were surveyed. Students responded to a student survey and a cognitive test. Administrators provided information about their respective institutions as well as student data. These students were followed up in 1973, 1974, 1976, 1979 and 1986. In addition, high school transcripts were collected in 1984. The follow-up surveys asked participants about their personal lives (marital status, children), further education outcomes, and work experiences including unemployment and military services. Participants also responded to items that measured their attitudes such as self-concept, goals, satisfaction, and community involvement (NCES, 2016f).

Two other articles merged different NCES datasets. Darolia and Potochnick (2015) merged NPSAS surveys with data from the current population survey to examine the effect of in-state resident tuition policy on undocumented student enrolment. Jagešić (2015) merged BPS and IPEDS surveys to examine the relationship between college student-peer ability match and educational aspirations. Finally, three articles merged a NCES dataset to datasets from other sources. Hearn and Belasco (2015) merged IPEDS and the Higher education general information survey to examine the institutional characteristics related to degree production in humanities in the past two decades. Taylor and Cantwell (2014) merged IPEDS, the National Science Foundation's WebCASPAR surveys, and the Council for aid to education survey to examine institutional factors predicting doctoral completion of international students. And Contreras and Contreras (2015) merged IPEDS with a non-NCES survey, the California community college data mart, to examine student outcomes of Hispanic serving institutions in California.

2.2 Issues and research questions studied

We examined what issues were studied with the NCES datasets and summarised the research questions of these articles into three categories:

a college access and choice

b student outcomes

c higher education finance.

More than one-third of the studies (10 out of 27) included in this paper explored one of the most critical problems that policymakers and institutional leaders encounter: college access and choice. These articles investigate issues, including how students aspire to, prepare to and enrol in postsecondary institutions. College access covers research topics such as the peer effect, college readiness, college aspiration, college preparation, college attendance, college under-match and major choice. Although some articles use high school-college transition datasets such as NLS:1972, NELS:88, ELS:2002 and HLS:09, the majority of the articles utilised ELS:2002 ($n = 6$) to examine topics relate to college access and choice, since ELS:2002 is the most integrated and longitudinal high school-college transition database up to date, which includes four waves of surveys from 2002 to 2012. HSLS: 09 is the most recent high school longitudinal dataset, but it is still underway with its second follow-up collection happening in 2016 (NCES, 2016b).

Student outcomes researched in the field of higher education include student academic performance, retention, attrition, completion and job placement. Seven articles examined topics on student outcomes at the student-level. These articles used datasets such as B&B:93/97/03, ELS:2002, NELS:88 and NPSAS:08. Another area on student outcomes in higher education explored issues of enrolment, degree completion, institutional climate and institutional revenue as well as higher education governance at the institutional level. These articles ($n = 5$) used IPEDS and their unit of analysis was university.

Of the articles reviewed, four examined topics on higher education financial issues, such as the impact of college costs, financial aid policy, financial aid application process and student loan and debt on student outcomes. These articles utilised datasets such as BPS:04/09 and IPEDS. In addition, one article (Darolia and Potochnick, 2015) that examined the effect of in-state resident tuition policy on undocumented student enrolment, is grouped into both the college access and choice category and the higher education finance category.

2.3 Analytical methods

As shown in Table 2, the articles used multiple research methods. The analytical techniques used are heavily influenced by disciplinary traditions, mainly econometrics, psychometrics, and educational research. Although these disciplines share basic fundamental concepts, they have different terminologies, notations, and reporting styles. Economists tend to focus on causal effects and unbiased estimates using quasi-experimental methods such as propensity score analysis, fixed effects, regression discontinuity, difference-in-differences and instrumental variables. Psychologists, however, aim to understand the measurement and constructs of unobserved factors using methods such as multivariate analysis, multilevel analysis, path analysis and structural equation modelling.

Table 2 List of articles published in 2015 using NCES large-scale secondary data to answer questions related to higher education in the USA

Database Used	*Topic Categories*	*Research Questions*	*Methods*	*Conclusions*	*Data Limitations*	*Article Reference*
B&B: 93/97/03	Student outcomes	Is there gender earning gap of college graduates in STEM fields?	Path analysis, sampling weights, listwise deletion	There is gender wage gap within the first ten years of employment		Xu, 2015
BPS:2004/2009	Higher education finance	What are the effects of loans on community college student persistence?	Propensity score matching, sampling weights	Borrowing is positively related to within-year persistence, but it is negatively related to 6-year persistence	Unable to measure the amount of the financial aid, unable to control all factors	McKinney and Burridge, 2015
BPS:2004/2009	Higher education finance	What are the FAFSA filing behavior among first-Year College Students?	Logistic regression, sampling weights	Later FAFSA filers receive less total grant aid compared to students who filed earlier	Unable to control all factors	McKinney and Novak, 2015
BPS:2004/ 2009IPEDS: 2003–2004	College access and choice	Does college student-peer ability match relate to educational aspirations?	Logit models, propensity score matching, sampling weights, listwise deletion	Students who have low SAT and are attending less selective colleges are more likely to decrease in future educational aspirations		Jagešić, 2015
ELS:2002	College access and choice	What factors relate to college undermatch?	Multilevel analysis, sampling weights, missing imputation (chained-equation imputation)	Background, attitudes and high school have significant influence on college undermatch	Nonresponse bias	Belasco and Trivette, 2015
ELS:2002	Student outcomes	How teachers'perceptions influence performance of immigrant and language-minority students?	Multivariate analysis, sampling weights, multiple imputations	Language-minority students are more likely to be negatively perceived.		Blanchard, and Muller, 2015

Table 2 List of Articles Published in 2015 Using NCES Large-Scale Secondary Data to Answer Questions Related to Higher Education in the USA (continued)

Database Used	*Topic Categories*	*Research Questions*	*Methods*	*Conclusions*	*Data Limitations*	*Article Reference*
ELS:2002	College access and choice	The effect of advanced math course taking on math achievement and college enrollment	Propensity score matching, sampling weights, multiple imputations	Advanced math course taking have positive impacts on math achievement and college enrollment	Data is outdated. Results may only generalisable to high school studentscohort 2002	Byun, et al., 2015
ELS:2002	Student outcomes	What is the impact of SES across educational stages?	Sequential logit modeling, multilevel analysis	Disadvantaged students have substantially lower college enrollment and completion rates compared to their high-SES counterparts.		Giani, 2015
ELS:2002	College access and choice	Is taking computer science courses at high school related to students' STEM major choices?	Logistic regression analyses, sampling weights, maximum likelihood (ml)	Students who took more computer science class in high school are more likely to choose STEM majors in both 4-year and 2-year colleges.		Lee, 2015
ELS:2002	College access and choice	Is racial differences in preferences for staying near family related to college attendance gap?	Ordered logit model, ordinary least-squares models, linear probability models, sampling weights, multiple imputation, multiple imputation with deletion method, listwise deletion	Compared to white students, Hispanic students are more likely to stay at home during college		Ovink and Kalogrides, 2015
ELS:2002	Student outcomes	What factors predict SAT preparation and higher SAT scores?	Multinomial logistic regression, generalised least squares regression	Students who have more cultural capital are more likely to participate in SAT preparation		Park and Becks, 2015

Table 2 List of Articles Published in 2015 Using NCES Large-Scale Secondary Data to Answer Questions Related to Higher Education in the USA (continued)

Database Used	*Topic Categories*	*Research Questions*	*Methods*	*Conclusions*	*Data Limitations*	*Article Reference*
ELS:2002	Student outcomes	What high school factors relate to Hispanic students high school graduation?	Multilevel analysis, listwise deletion	School safety and same-race friendships is positively related to high school graduation.	Unable to measure the degree or quality of the variable	Reed, 2015
ELS:2002	College access and choice	How different ways of estimating college undermatch can produce differential findings?	Logistic regression, sampling weights, multiple imputations	Various ways of estimating college undermatch can produce differential results		Rodriguez, 2015
HSLS:2009	College access and choice	The impact of close friends who are college bound on students' college readiness	Propensity score analysis, missing imputation (STATA "ice")	Having a college-bound friend is positively related to college readiness generally	Use observational data to infer causal effects	Alvarado and An, 2015
IPEDS and California Community College Data Mart	Student outcomes	What are the student outcomes of the Hispanic serving institutions (HSIs) in California?	Descriptive statistics, listwise deletion	Most HSIs have lower college completion rates than non- HSIs.	Nonresponse bias	Contreras and Contreras, 2015
IPEDS and Higher Education General Information Survey	Student outcomes	Do institutional characteristics relate to degree production in humanities?	Fixed-effects, random-effects, fixed-effects vector decomposition	More financial resources are related to humanities degree production overtime		Hearn & Belasco, 2015
IPEDS: 2000–2001 through 2012–2013	Higher education finance	What are the effects of sticker-price changes on net tuition revenue?	Fixed effects	In the recession, sticker-price fell is related to net tuition revenue increased		Altringer and Summer, 2015
IPEDS: 2002	Student outcomes	Do campus educational contexts and civic participation predict campus action?	Logit regression model, listwise deletion	Campus curricular offerings was associated with campus action	Small sample size	Barnhardt, 2015

Table 2 List of Articles Published in 2015 Using NCES Large-Scale Secondary Data to Answer Questions Related to Higher Education in the USA (continued)

Database Used	*Topic Categories*	*Research Questions*	*Methods*	*Conclusions*	*Data Limitations*	*Article Reference*
IPEDS:1987–2006	Student outcomes	Do state higher education governance structures influence nonresident tuition rates?	Time-series cross-sectional (TSCS), dynamic fixed-effect panel (DFEP) modeling	Nonresident tuition has increased faster in states with low nonresident tuition	Unable to measure the academic performance of participants	Titus, Vamosiu, and Gupta, 2015
IPEDS:1990–2006 NSF:WebCASPAR Council for Aid to Education	Student outcomes	What institutional factors predict doctoral completion by international students?	OLS regression analysis, fixed effects, listwise deletion	The number of international students who earned doctoral degree has increased for both public and private universities in the last decade		Taylor and Cantwell, 2015
IPEDS:2002–03 to 2012–13	Student outcomes	Do state appropriations decline relate to nonresident freshman enrollment?	Fixed effects panel models, multiple imputations, listwise deletion	Declines of state appropriations positively relate to nonresident freshman enrollment	Unable to control all factors that relate to the dependent variable	Jaquette and Curs, 2015
NELS:1988	College access and choice	Is there rural–nonrural differences in college attendance?	Multinomial logit models, sampling weights, missing imputation	Rural students are less likely to attend selective institutions compared to their nonrural peers	Data is outdated	Byun, Irvin, and Meece, 2015
NELS: 1988	Student outcomes	Are the expected incomes different between college students and their peers in employment?	Ordinary Least-Squares models, fixed effects regression model, sampling weights, listwise deletion	College students make better predictions of their future income than their peers in the labor force	Use predicting data to infer unobserved	Jerrim, 2015
NLS:1972, ELS:2002	College access and choice	The relation between high school GPA and college attendance	Multinomial logit models, sampling weights, missing imputation	High school GPA became more predictive of college enrollment over time	Measures of constructs were not standardised over time	Archibald, Feldman, and McHenry, 2015

Table 2 List of Articles Published in 2015 Using NCES Large-Scale Secondary Data to Answer Questions Related to Higher Education in the USA (continued)

Database Used	*Topic Categories*	*Research Questions*	*Methods*	*Conclusions*	*Data Limitations*	*Article Reference*
NPSAS: 2008	College access and choice	Is student characteristic related to online course enrollment for STEM majors at community college?	Logistic regression, sampling weights, listwise deletion	Race and gender are more important predictors of online enrollment than other characteristics for community college students	Unable to control all factors that relate to the dependent variable	Wladis, Hachey, and Conway, 2015a
NPSAS:2000, 2004, 2008, and 2012 Current Population Survey (CPS)	College access and choice, Higher education finance	What is the effect of in-state resident tuition (IRT) policy on undocumented student enrollment?	Difference-in-differences, sampling weights	IRT policies have a positive effect on undocumented immigrants' college enrollment	Using a proxy to identify the unobserved variable	Darolia and Potochnick, 2015
NPSAS:2008	Student outcomes	Is gender, race, citizenship and English-as-second-language (ESL) related to online course enrollment?	Logistic regression models, sampling weights, listwise deletion	Nontraditional student characteristics are more likely to predict enrollment in online courses		Wladis, Hachey, and Conway, 2015b

Note: B&B = Baccalaureate & Beyond; BPS = Beginning Postsecondary Survey; ELS = Educational Longitudinal Study; IPEDS = Integrated Postsecondary Education Data System; HSLS = High School Longitudinal Study; NELS = National Education Longitudinal Study; NLS = National Longitudinal Study; NPSAS = National Postsecondary Student Aid Survey

Using econometrics methods, Schneider et al. (2007) provided a brief summary on how to estimate causal relationship using observable data. For example, propensity score matching creates comparable samples from treatment and comparison groups and corrects selection bias by controlling for the observable differences between the groups. Difference-in-differences method estimates causal relations by comparing the average change over time for the treatment group to the average change over time for the control group (Angrist and Pischke, 2008).

In psychology, multilevel analysis is an effective method to analyse nested data. It partitions the variance and examines relationships at different levels as well as cross-level interaction effects (Raudenbush and Bryk, 2002). Path analysis can be used to test direct and indirect effects between observed variables (Kline, 2011). Multivariate analysis is an approach for more than one outcome variables (Sharma, 1996). Structural equation modelling can be used to incorporate latent factors and to study relationships among them.

Of the 27 articles, 19 used one analytical method. The most used methods were logistic regression (n = 6), propensity score analysis (n = 3), multinomial logit models (n = 3), multilevel analysis (n = 2), difference-in-differences (n = 1), fixed effects (n = 1), path analysis (*n* = 1), multivariate analysis (*n* = 1) and descriptive statistics (*n* = 1). Eight articles used more than one of the above methods to analyse the data.

Propensity score analysis (PSA), particularly propensity scoring matching has gained attention recently for causal inference. Since PSA is the most frequently used casual inference technique among the selected articles, we further examine articles that applied PSA in order to provide practical suggestions on how PSA was used in the NCES postsecondary datasets. We did this following Garrido et al. (2014) suggested methods for conducting PSA in six steps:

1 *choose variables to include in the propensity score*

2 *balance of propensity score across treatment and comparison groups*

3 *balance of covariates across treatment and comparison groups within blocks of the propensity score*

4 *choice of matching and weighting strategies*

5 *balance of covariates after matching or weighting the sample*

6 *interpretation of treatment effect estimates (p.1701).*

We analysed the three articles that used PSA based on these recommendations. Of them, one mentioned conducted balance testing without including any statistics on balance checking. Three articles reported using PSA with some recommendations of Garrido et al. (2014). All three articles that used PSA technique (Alvarado and An, 2015; Byun et al., 2015; McKinney and Burridge, 2015) described the process in four steps. First, propensity scores are calculated by predicting group membership (treatment vs. control) with covariates using logistic regression. Propensity scores are the probabilities of being the treatment group conditional on the covariates. Next, based on the propensity scores, cases from the treatment and control groups are matched. There are different algorithms for matching including exact matching, nearest neighbour matching, neighbour matching with a caliper, kernel matching, etc. Third, check balance between the treatment and control groups. Finally, data from the matched samples for the treatment and control groups are analyse to obtain the group differences on the outcome variables. Such group differences are often referred to as the causal effect.

2.4 Data conditioning

2.4.1 Weighting

Most of NCES surveys use complex sampling designs, including stratification, clustering, and oversampling. Some particular studies such as, NLS:1972, NELS:88, ELS:2002 and HLS:09 were conducted by using a two-stage (school and students) sampling: schools were sampled in the first stage and students were sampled within each selected school in the second stage. An average of 18–25 students per school were selected (NCES, 2016c–f). In addition, these datasets oversampled certain groups, such as Black (Riccobono et al., 1981), Asian and Hispanic students (Curtin et al., 2002; Ingels et al., 2005).

In the analysis of the large-scale secondary data, it is suggested that appropriate weights be used to reflect the sampling design, so that the results can generalise to the population (Hahs-Vaughn, 2007; Thomas et al., 2005; Thomas and Heck, 2001). Among the 27 articles we selected, 22 used data from surveys with a complex design. Of them, 18 reported using sampling weights in the analysis. We chose three articles to provide examples on reporting weights. McKinney and Burridge (2015) examined the effects of loans on community college student persistence using BPS:04/09. They discussed the data structure, complex sampling design, and the logic of using weights based on the literature. They reported weighted and unweighted descriptive statistics (number of observations) of the entire sample and subsample, as well as analysis results using weighted and unweighted samples. Darolia and Potochnick (2015) did not report the data structure and justification of using weights. Rather, they reported only weighted descriptive statistics (mean and standard deviation) of the variables. When reporting results, they compared coefficients from weighted models, unweighted models and the models adjusted for standard errors due to clustering. Jagešić (2015) examined the relation between student-peer ability match and educational aspirations using BPS:04/09, and reported the multiple stage sampling structure of BPS and the reasons for weighting.

2.4.2 Missing data handling

Missing data handling is a critical step when conducting research using secondary data. For analysis with missing data, it is important to understand missing data mechanisms. Rubin (1976) summarised missing data in three types: missing completely at random (MCAR), missing at random (MAR) and missing not at random (MNAR). MCAR is missing data that do not relate to other observed or unobserved variables and missing is unsystematic. MAR is missing data related to other observed variables. MNAR is missing data related to the dependent variable or unobserved variables. These three missing data mechanisms are assumptions that guide the selection of missing data handling techniques (Baraldi and Enders, 2010; Manly and Wells, 2015).

Prior studies suggest many ways to deal with missing data in educational research, such as listwise deletion, pairwise deletion, mean substitution, maximum likelihood and multiple imputation (Baraldi and Enders, 2010; Graham, 2009). Listwise deletion drops all the cases with missing data. Pairwise deletion drops cases with missing based on analysis. Mean substitution replaces missing data with the means of the variables. These three missing handling techniques are based on the assumption of MCAR and results can be biased when MCAR is violated. Maximum likelihood (ML) and multiple imputation (MI) are two modern missing data techniques that are recommended by recent literature and they can produce unbiased results under the assumptions of MCAR and MAR (Baraldi and Enders, 2010; Peugh and Enders, 2004).

Of the 27 articles analysed, nine did not report any information on missing data handling. Eight reported using listwise deletion, one reported using ML, and nine reported using MI. Since MI is the most frequently used missing data technique among the selected articles, we chose the articles which used MI to provide practical suggestions on missing data handling. We did this following Manly and Wells's (2015) suggested use of multiple imputation for missing data reporting practices in nine steps:

a *report rates of missing data*

b *report reasons data are missing*

c *report evidence of ignorable patterns or assumptions* d *report variables used in the imputation phase*

e *communicate the algorithm/procedure*

f *report the number of imputations*

g *indicate pooling procedures*

h *compare observed and imputed values*

i *discuss discrepancies between multiple analysis methods (pp.400–404).*

Based on these recommendations, we analysed nine articles that used MI. Of them, six mentioned using MI without including any of the recommended reporting practices. Three articles reported using MI with some suggestions of Manly and Wells (2015). We discussed these three articles in detail as examples of missing data reporting. Ovink and Kalogrides (2015) examined the racial differences in preferences for staying near family related to college attendance gap between Hispanic and other groups using ELS:2002. They reported that missing data were due to non-responses and created five imputed datasets. Then, they described the means of variables being imputed and compared the means of the covariates before and after imputation. They also compared regression results using three different ways of handling the missing data: imputed values of the dependent variable, multiple imputation with deletion of the imputed values of the dependent variable, and listwise deletion. Alvarado and An (2015) examined the impact of close friends who were college bound on students' college readiness using HSLS:09. They reported the missing data mechanism and percentage of missing data, and provided Stata syntax used for imputation. In addition, the pooling procedures were described. Jaquette and Curs (2015) used IPEDS to examine the effect of state appropriations decline on nonresident freshman enrolment. They used both listwise deletion and MI to handle missing data. Missing rates of variables were reported, as well as the sample sizes before and after listwise deletion. The authors discussed that missing data is not random as a limitation.

2.5 Data limitations

Here, we discuss the four most-frequently reported data limitations. Three articles reported that they could not control for all variables, which may relate to the dependent variable due to the limitation of secondary data (McKinney and Novak, 2015; Jaquette and Curs, 2015; Wladis et al., 2015a). McKinney and Novak (2015) examined the financial aid application among college students and they reported the data limitations by explaining the mechanism of omitted variable bias, which could occur if models were unable to control for factors that relate to the dependent variable. Based on the literature, they reported that high school counsellor was an important factor that influences financial aid application, but they were unable to control it due to the secondary data. Jaquette and Curs (2015) reported that they could not control for all variables that related to the dependent variable, nonresident freshman enrolment. They listed potential omitted variates that may bias their results, such as college athletics, natural resource, or tuition reciprocity agreements. Similarly, Wladis et al. (2015) examined what student characteristic predict online course enrolment for STEM majors at community college. Due to data limitation, they reported that they were unable to control for variables that may relate to online enrolment, such as institutional policies or online learning resources.

Three articles mentioned that they were unable to measure the quantity of the variables. For example, McKinney and Burridge (2015) reported that they only knew the type of financial aid, but were unable to measure the amount of financial aid. Reed (2015) investigated high school factors that associated with Hispanic students' graduation and she reported that she was unable to measure the degree or quality of the school resources provided to students. Titus et al. (2015) examined whether the state higher education governance structures influence nonresident tuition rates. They reported that they were unable to measure the academic performance of participants due to data limitation.

Two articles discussed nonresponse bias as a data limitation. Belasco and Trivette (2015) examined factors relate to college undermatch. They reported missing data due to nonresponse and they were concerned that the missing data were not at random. Contreras and Contreras (2015) reported that several institutions did not response to the survey which influence the results of the study.

Another two articles reported that their data were outdated. Byun, Irvin and Bell (2015) examined the effect of advanced math course taking on math achievement and college enrolment using ELS:2002. They reported that the data were outdated and results may not be generalisable to recent high school students. Byunet al. (2015) using NELS:88 to investigate the rural–nonrural differences in college attendance. They reported that their dataset was old and provided an explanation of why they used that dataset. There were newer high school students longitudinal datasets such as ELS:2002 and HSLS:09, but these two datasets did not have the variables they needed.

3 Discussion

National Center for Education Statistics collects and analyses data on the program of education in the USA. Its statistics and reports are used for multiple purposes by Congress, federal agencies, state and local officials, business leaders, scholars and researchers, and the general public to formulate programs, distribute resources, monitor services, research significant topics and inform educational decisions-making. In this paper, we focus on peer-reviewed journal articles published in 2015 that use NCES's postsecondary education survey data. These studies are designed to answer research questions that are important to US higher education in the areas of college access and choice, student outcomes and higher education finance.

Based on the review of the 27 published articles, we found that the most commonly used NCES postsecondary surveys are ELS:2002 and IPEDS, followed by BPS:04/09, NPSAS, NELS:1988, B&B:1993/1997/2003 and HSLS:2009. However, several NCES postsecondary surveys are not used in this sample of articles, such as the high school and beyond (HS&B), career/technical education statistics and National Study of Postsecondary Faculty. Moreover, our findings suggest that commonly issues studied using the NCES postsecondary datasets are college access and choice, student outcomes and higher education finance. In addition, our analysis indicates that these articles applied appropriate and advanced analytical methods and the majority of them took into consideration the complex sampling designs and data structures of these NCES surveys.

National Center for Education Statistics provides rich large-scale secondary data for researchers interested in higher education issues, usually with tens of thousands of participants over time. One of the biggest advantages of using NCES survey data for research is that the samples are large and are representative of the population. Therefore, results can be generalised to the population. In addition, researchers may be interested in a specific subsample, or comparing subsamples and as such, since NCES survey data include different demographic and other information on the participants, it is easy to dissect the sample and conduct analysis for subsamples. The quality of NCES data is usually high, partly due to the careful planning and rigorous design of the surveys that involve content and survey design experts. Despite that NCES datasets are still a rich source of information to answer important questions related to postsecondary education, these datasets remain underutilised for scientific research. For example, we identified only 27 articles that were published in 2015 that used data collected by NCES.

National Center for Education Statistics categorises its surveys and programs into assessments, early childhood, elementary/secondary, international and postsecondary (http://nces.ed.gov/surveys). Data, either publicly accessible, or for restricted-use, are available for researchers. For each survey/program, there are reports, technical manuals and other materials that would help users to understand the assessment design, sampling procedures, specific questions asked and data coding. In addition, NCES offer tools that can help researchers to easily navigate their data products and locate relevant data quickly. For example, researchers can find information about specific institutions, compare institutions, obtain summary data or customise data files for analysis using the tool for IPEDS (http://nces.ed.gov/ipeds/datacenter). Some programs even offer syntaxes written in different programming languages to facilitate data management and/or analysis (e.g. https://nces.ed.gov/surveys/international/ide).

Publishing using secondary data can be difficult for researchers, partly because the variables needed may not always be available or may not exactly match the constructs in a theoretical framework. Another challenge lies in the complexity of linking the data. Although technically linking different databases is possible (Dynarski, 2014), it can pose significant difficulties to researchers, especially for those who majorly conduct substantive research and are less familiar with how to manage large-scale data. For example, data may be collected from students as well as from administrators of the schools. However, data may exist in different datasets and, thus, need to be linked, which involves considerations of data disaggregation, matching, and/or (re)creation of weight variables. If the data are longitudinal, additional considerations are added, especially when students transfer among schools during the studied period. The reports and technical manuals accompanying the survey programs are useful, but they can be daunting and lengthy. Some surveys use naming conventions for variables and as a result, variable names are generic masking meanings. Due to these difficulties, we recommend higher education researchers to work with quantitative methodologists in order to integrate substantive research and advanced methods to understand college access and choice, student development and success and other outcomes.

To increase the use of data by researchers, we recommend that NCES, in collaboration with methodologists, develop tools that can be more easily accessed and used by researchers. Whereas some tools provided by NCES are available for summary and descriptive statistical analysis, there are no tools for sophisticated statistical analyses. Of the 27 articles we analysed, some used propensity score matching to examine causal relationships (Alvarado and An, 2015; Byun et al., 2015; McKinney and Burridge, 2015); some use sophisticated methods such as multiple imputation to address missing values (Alvarado and An, 2015; Jaquette and Curs, 2015; Ovink and Kalogrides, 2015). These techniques involve relatively complex programming for statistical analysis. Since researchers are already using these methods, NCES may consider having a repository where researchers can share their programs and syntaxes for statistical analysis, similar to the bibliography search tool (http://nces.ed.gov/bibliography/) that NCES collects publications using its datasets.

It is noteworthy to mention that linking NCES surveys with other data can be very useful. For example, Dynarski (2014) and Loeb (2014) realised the potential promise that administrative data hold as a complement to NCES surveys. They argued that linking data from NCES with administrative data would reduce the effort of collecting data already available from other sources. In particular, Dynarski recommended that NCES should supplement its surveys with administrative data, focusing efforts on data not contained in existent administrative data. For instance, NCES could use data from the national student clearing house and/or the internal revenue service containing relevant information on college student spells and college identity. She also argued that these linkages would help turn NCES cross-sectional studies into longitudinal studies. In the same vein, Loeb (2014) suggested that both NCES data users and states benefit from these linkages. While she listed many benefits for NCES users, the most important one is that administrative data could serve as a post-NCES-data or follow-up. For instance, linking data from the early childhood longitudinal study, which ends at kindergarten, to student identification numbers in state administrative data would allow NCES users to follow the development of these children through elementary and secondary education. The state also would benefit from these linkages by having access to data from non-school sources which are difficult for the state to collect. For example, state policymakers may use information from parents' reports collected by NCES to better understand students' needs and, thus, make informed decisions. In sum, we anticipate that there will be more research making use of linked databases. In November 2013, the National Academy of Education held a workshop to examine current and potential uses of NCES longitudinal surveys and provided recommendations on how to enhance the role of NCES's longitudinal survey program to better serve the changing needs of the research community in light of the change in data collection, technology, and population. At this workshop, NCES was praised for its effort in conducting and maintaining the longitudinal surveys. The objective of this program is to obtain data and analysis related to the pathways of high school students as they grow into adulthood and follow different paths to either continue with postsecondary education or enter the workforce (NCES, 2016a). These surveys also collect data on environmental variables that impact students' development including personal, familial, social, institutional, and cultural factors. These longitudinal surveys not only allow the examination of changes over time and how changes are related to different personal and environmental variable, but also make comparisons across generations possible.

Weaknesses of the NCES longitudinal surveys were also identified and recommendations made at the workshop. In particular, it was determined that the most salient shortcoming of NCES surveys lies in the infrequency of its surveys, which makes it difficult to capture the short-term changes that may arise from a shift in national policy (Dynarski, 2014; Warren, 2014). Although NCES samples are nationally representative, they may not be reliable enough to measure variation across states due to the small sample sizes in each state (Dynarski, 2014). In addition, NCES surveys are not very useful to draw international comparisons (Warren, 2014). To overcome some of these shortcomings, Warren (2014) recommended NCES emulate successful examples such as the Census Bureau and the National Opinion Research Center. Specifically, he suggested that NCES should:

a adapt the changing nature of research community

b seek to contain state representative samples

c invite researchers and other governmental agencies to develop new survey modules, design, and content that feature a new innovative mode of administration.

Although NCES survey data, whether cross-sectional or longitudinal, are usually collected in natural settings, they can be used to inform or complement randomised controlled trials (RCTs). For example, Byun et al. (2015), using ELS:2002 data, found that advanced math course taking has positive impacts on math achievement and college enrolment. Based on the findings, a RCT can be designed to study the effect of particular advanced math course offering programs.

In sum, the work by NCES is broad, complex, far-reaching, and rigorous. Our intention with this paper is to inform researchers unfamiliar with NCES datasets about the range of data available that can inform research and practice in postsecondary education in the USA. To accomplish this, we analysed peer-reviewed published research articles in 2015 that use NCES datasets for postsecondary research. We concluded with a series of recommendations for both users and leaders developing these surveys in order to maximise their utility. These recommendations, if adopted, will undoubtedly result in more use of NCES data for research.

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