**2018 NCES Data Institute Research Reports- Webinar Script**

1st Speaker

Good afternoon, I am Jihye Kwon, Analyst for Co-Curricular Assessment and Research at Northern Kentucky University. On behalf of our group, I present our NCES Data Institute Capstone project today. Our project focuses on differences in student borrowing, particularly, how student race/ethnicity groups have different borrowing behaviors as well as different income groups over the past 2 decades.

Racial gaps in educational access and attainment have persisted throughout the history of American higher education. While more students of color participate in higher education now than ever before, inequities still remain. In this regard, our study examines the federal student loan borrowing practices for undergraduates over the last two decades, by income and race/ethnicity. More specifically, we look at how borrowing levels and the incidence of borrowing have changed over time. Our project contributes to the policy and research discussions by focusing specifically on longitudinal borrowing patterns across student subpopulations.

Student loan continues to be a critical role in financing college for many students. About 40% of students finance their education through student loan. Several prior studies have focused on students' borrowing behaviors by race/ethnicity and socioeconomic status. However, a lot of these papers have looked at differences in borrowing in terms of the amount borrowed, and especially using cross-sectional data. But, there seems to be less understanding of how the rate of borrowing varies and how those rates have changed over time for different student populations. In that regard, our study does contribute to the conversation on racial/income gaps in borrowing by highlighting that these disparities aren't static - in some cases, they're growing - and this is an important factor to consider within the broader policy conversation of disparities in student debt loads/default rates.

Based on current student debt issues and literature, we created two research questions for our projects. First question is How have the odds of federal student loan borrowing changed over the last two decades for undergraduate borrowers, across income and race subgroups? Secondly, To what extent has the average annual amount of federal student loans borrowed changed over the last two decades, by income and race for undergraduate borrowers?

We use data from six administrations of the National Postsecondary Student Aid Study (NPSAS), a nationally representative survey of undergraduates. NPSAS features administrative institutional and federal financial aid data from the National Student Loan Data System. We use all NPSAS datasets publicly available from the National Center for Education Statistics: 1996, 2000, 2004, 2008, 2012, and 2016.

To investigate how federal loan borrowing varies across racial groups, we conducted logistic regression on a binary measure of whether a student borrows federal Title IV loans (excluding The Parent Loan for Undergraduate Students (PLUS) loans). We chose to use white, non-Hispanic students as a reference group because they are the largest student population and often used as a reference group in other student loan studies. For income variable, we chose a low-income student group as a reference group. In addition to these two independent variables, we also included students' financial dependency and institutional sector in our model. In addition to the regression analysis, we conducted a descriptive analysis on amount of federal loan borrowing by race/ethnicity and family income.

In Table 1, we present estimates from logistic regression models that predict the likelihood of borrowing across various student characteristics after controlling for income, institutional sector, and dependency status. Our estimates indicate that race/ethnicity is significantly associated with borrowing federal loans. In 1996, all students of color have lower odds of borrowing compared to white students. However, starting with NPSAS:00, black, non-Hispanic students have consistently greater odds of borrowing after controlling for students' family income, type of institution attended, and financial dependency status. By 2016, the odds of borrowing for black students are 1.59 times higher than for white students. Hispanic students have consistently lower odds of borrowing. In 2016, the odds of borrowing for Hispanic students are 0.67 times lower than white students. Our estimates suggest that Asian students also have lower odds of borrowing; however, we interpret the estimates for this and other racial subgroups with caution because in some years the overall sample representation falls below 10%.

Earlier research suggests that black students were equally as likely as white students to borrow the maximum amount authorized by the Higher Education Act (HEA) until 1992, after the 1992 HEA reauthorization introduced unsubsidized loans, expanded subsidized loan eligibility, and increased federal loan limits for students after their first year. These policy changes were associated with an increase in overall borrowing, particularly by dependent students from the middle class, suggesting that the terms of student loans may affect student borrowing decisions. Within our timeframe of interest, changes in the odds of borrowing between NPSAS:96 and NPSAS:00 may reflect policy changes enacted in 1998, such as lower interest rates on loans and a revised needs analysis formula to determine a student's expected family contribution.

This figure shows how different students' ethnicity groups borrow compared to white students which are adjusted in 2016 dollars.

For black students, except 1996, they continuously borrowed more than their white peers and the gap has not been narrowed. Hispanic/Latino students borrowed less than white students, overall gap has narrowed over the past 20 years. For Asian students, amounts borrowed are similar. For more than one race of students and Hawaiian/Pacific Islander students, they borrowed more than their white peers. Lastly, American Indian and Alaska natives borrowed less than white students.

This second figure shows how much loan students borrowed by different income groups over the last 2 decades. As you can see, the higher their family earns, the less they borrow. One interesting trend is that the gaps between groups has narrowed until 2012. In 2012, every group borrowed between $6500 and $6900. For all groups, however, in 2016 the gap has widened again. In addition, regardless of different income levels, the overall amount borrowed significantly increased.

Our analysis finds that racial/ethnic differences in federal loan borrowing behavior have diverged during the last 20 years, even after controlling for family income, dependency status, and institutional type. For example, while Hispanic students are increasingly less likely to borrow compared to their white peers; black students are increasingly more likely to borrow. These results complement cross-sectional analyses that found black students from lower income families are more likely to borrow than white students in the same income group, and that the difference between how much black and white students borrow is largest among students with the wealthiest parents. Given that high levels of student loan debt may affect student degree completion, family formation, and other long-term outcomes, the evidence that black students are more likely to both borrow - and borrow more than their white peers - suggests that the current loan-based financial aid system is likely to have disproportionate consequences for black borrowers both during and after college. These patterns also reflect broader trends in wealth disparity.

Regarding differences by student family income, students with moderate annual incomes are now borrowing at rates similar to the lowest-income students. The gap in annual borrowing amounts between low- and high-income students narrowed, then re-grew. Overall, all student groups are borrowing more to pay for college education. This pattern aligns with tuition increases and stagnant growth in student grant aid resources. The increase in student loan limits also plays a role in higher annual average debt levels. Our results provide additional evidence of systematic differences in the strategies students use to finance their postsecondary education by illuminating longitudinal evidence of racial differences in student borrowing.

2nd Speaker

The study examined if Pell Grant eligibility policies need to be revised to ensure that the right students are receiving the financial aid they need in order to stay in college. We found that students who just missed the cutoff for a Pell Grant faced similar barriers as those who are eligible for a grant and could potentially benefit from additional financial assistance.

And, as a group, when all initially discussed our research interests, we saw an equity focus in each of our interest areas. So, right from the get-go, the project was allowing us to tap into our research interests. As a group we decided to focus on researching the Pell Grant because it is designed to support low-income students.

A relatively high proportion of college students receive Pell Grants. Over 1/3 of students at public institutions receive them. lot of students receive Pell Grants. A high percentage of students receive a Pell Grant at both 2- and 4-year institutions.

As we looked into the literature we saw some themes emerge related to the Pell grant. We know that it is awarded to millions of students every year, across the public, private, and 2- and 4-year postsecondary sectors. And, importantly, we know that tuition assistance one of the important factors in helping students reach the finish line.

But we were really interested in the question—who gets Pell money? How does the Federal government determine if you need Pell funds?

The federal Pell Grant program provides need-based grant aid to college students. This program is designed to assist low-income students and families afford college.

There is an index that is calculated called the Expected Family Contribution, or the EFC. This is a calculation based on a family's income, assessed, with deductions, and this is used to determine whether a student is eligible for Pell or not. After calculating what a family's EFC is, it is compared to a threshold set by the federal government. If a family's EFC calculation falls below a threshold, the student qualifies for Pell. If a family's EFC falls above a threshold, the student is not eligible for Pell.

In recent years, Congress has redefined what "low-income means" in terms of how a student qualifies for a Pell Grant. More specifically, Congress changed the calculation of EFC. In the past, a student's family could make $32,000 annually and that would be proportional to an EFC of $0. Now, a student's family making 20,000 a year has an EFC proportional to $0.

In 2012 a number of changes were instituted to its defined student constituents, including lowering the eligibility window from 18 FTE semesters to 12 and further reducing the minimum family income level to qualify for a $0 expected family contribution (EFC) to $20,000 from $32,000 (U. S. Department of Education, 2012). These changes resulted in significant savings for the congressional budget, but, in doing so, adds constraints for the types of students that would be eligible to participate in the program.

Our research question revolved around this idea of maybe there are some students that are really close in their economic standing. Students that are just below, and just above the EFC cutoff mark. We were doing a sort of simplistic, pseudo difference-in-differences modeling. We were saying, we assume that folks just above and just below the cutoff mark are very similar. And the one main difference between them is whether they received Pell funds or not. So, if we control for everything else, do we see an association between receiving Pell and first-year persistence?

Throughout the course of our training in NCES sample surveys, we learned the strengths and weaknesses of each of the surveys, and this allowed us to determine that the BPS was the right dataset for our research question.

We examined a cohort of students, and restricted it to public institutions and those who actually applied for federal aid.

We examined the demographic characteristics of these students and the descriptive patterns of their first-year persistence based on whether they were above or below the Pell cutoff. We also did some very simple logistic regressions.

Were able to do these descriptive and simple inferential analyses with a tool provided on the NCES website called Power Stats. One of the things I'll note is that the survey studies were accessible through Power Stats, which was an interesting tool to use. For those of you who use your own statistical analysis software such as Stata, SPSS, or SAS, some of the older survey studies have public-access data available. With those, you can download the public-access data because the dataset is older, and then you have all of the control over how you manipulate variables and analyze the data. That is something I may have done differently.

So, to reiterate, our outcome of interest was first-year retention. Did students persist into their second year of study?

The IV was a dummy variable of whether the student was above or below the EFC cutoff. And we controlled for various background factors that we thought would have an impact on retention

In the time period of our cohort (2011-12 cohort of students), the EFC cutoff amount was approximately $5,000. We decided to use an analytic window of 3,000 dollars. So, if folks were between 2,200 and 5,200 they were in the below cutoff group, and if folks were between 5,200 and 8,200 they were in the above cutoff group.

Descriptively, we didn't find statistically significant differences between the percentage of students that persisted, when comparing those who were above and below the Pell cutoff marks. You'll see that at four-year institutions, retention was 89 and 90 percent in our sample. Among two-year institutions there were some small differences, but these were not statistically significantly different.

We did not find any statistically significant association between students that were receiving Pell vs not receiving Pell in retention. We did find some statistically significant differences in association between some of our control variables and retention.

- For example: The only significant predictors of retention were:
  - Gender (male had 54 percent increased odds of NO retention)
  - High school graduation year (bet ween 2007 and 2010 had 2.47** times the odds of NO retention)
  - Institution level (two-year had 2.75** times the odds of NO retention)

By looking into those findings that were statistically significant, it prompted us to think about how we might continue this research. One of the first steps we would consider was trying to obtain a restricted data license so we would have access to the raw data. This would allow us to have a lot more control over the types of inferential analyses we did and our construction of certain variables for analysis.

<u>3rd Speaker</u>

Our group's focus for the Data Institute was on remedial education in college and we used data from the Education Longitudinal Study to analyze the student characteristics associated with enrollment in remedial courses, especially remedial math.

Some background on why we thought it was important to focus on this topic: A recent NCES report found that one third of new college students enroll in at least one remedial course, and this rate is higher at two-year colleges.

Most research has focused on the outcomes of enrolling in remedial courses or not. Results have been mixed, with most studies finding that remedial course enrollment has a negative effect on outcomes such as transfer and bachelor's degree attainment. There have however been some rigorous studies finding positive effects. The Long and Boatman article provides a good concise review if you're interested.

We're more interested in beginning to examine questions related to how students end up in remedial courses in the first place.

This interest led us to two specific research questions.

First, we were interested in whether there was a significant association between math course-taking in high school and remedial math enrollment. States are increasingly requiring high school students to complete Algebra II, often on the basis that this will ensure that students are "college-ready." So, we looked at the relationship between completing Algebra II and remedial math enrollment.

Our second question followed from some of our findings from analyzing our first research question. Studies of remedial education often focus on demographic characteristics and academic preparation and their relationship to remedial enrollment. We hypothesized that noncognitive characteristics might also be playing a role, and we had several good measures of specific noncognitive attributes in our dataset to test this hypothesis.

We used the public-use micro-data from the Education Longitudinal Study of 2002. This study sampled a nationally representative sample of 10th graders in 2002, and administered surveys to these students, their parents, teachers, and high schools. Students also completed math and reading and noncognitive assessments. Students were followed for 10 years, and NCES conducted follow-up surveys in 2004 (when an on-time student would have graduated high school), 2006, and 2012 (which would be four years after an on-time student graduated from a four-year college). NCES also collected high school and college transcripts.

ELS is a great dataset for studying high school to college transition, which is essentially the part of the educational pipeline we were interested in. We were able to use transcript data to identify students' high school and college course-taking patterns, which are likely to be more accurate than student self-reports. ELS also included those noncognitive assessments that can be hard to come by otherwise.

We limited our sample to students who enrolled in college and had non-missing data on key variables and we weighted our data to account for NCES's complex sampling design and ensure that our findings were nationally representative.

We used slightly different methods for each research question. For the first question of the association between high school math course and remedial math enrollment, we estimated logistic regression models with and without propensity score weights for the propensity to complete a particular level of high school math. Our dependent variable was a binary variable for whether or not a student who enrolled in college enrolled in remedial math. We operationalized our independent variable of the highest high school math course taken in three categories: highest course taken was *below* Algebra II, highest course taken *was* Algebra II, and highest course taken was *above* Algebra II. We also controlled for students' demographic characteristics, other measures of academic preparation like standardized test scores, noncognitive measures like math self-efficacy, family characteristics like income and parent education, and high school characteristics like urbanicity. We estimated an overall model for all college enrollees and separate models for students who enrolled in four-year colleges and students who enrolled in two-year colleges.

This graph breaks out the percent of students who enrolled in remedial math based on the highest-level math course taken in high school.

Overall, 31% of students in our sample enrolled in remedial math.

Not surprisingly, students who completed higher levels of math in high school enrolled in remedial math in college at lower rates.

We see the same pattern of enrollment for all three of our samples, but the highest rates of enrollment in remedial math are in two-year colleges, which again is not surprising.

Results from our regression models enable us to assess whether these descriptive relationships hold after controlling for observable factors that are likely to be related to both math course-taking in high school and remedial enrollment in college.

This table presents the results from our 12 models, 4 models for each sample. We only report the coefficients for the key independent variable of interest, math course taken relative to a course below Algebra II. Coefficients are presented as marginal effects so each one represents a percent change in the likelihood of remedial math enrollment.

For example, without any control variables or weighting, we see that taking Algebra II in high school is associated with a 10.7% reduced likelihood of enrolling in remedial math in college, and that this association is statistically significant. The size of the association decreases and becomes non-significant with the introduction of control variables and the propensity score weights.

Looking at the most robust model, we see that in general there was no significant association between high school math course and remedial math enrollment after controlling for a host of other characteristics and using propensity score weights.

We do see differences in magnitude and significance of associations based on model specification, and we saw more of this in some additional models that we ran but didn't show here. What all of this tells us is that association between high school course-taking and remedial math enrollment is sensitive to model specification and that many other factors also drive remedial math enrollment. Policies defining completion of Algebra II as college ready may not be enough to reduce remedial math enrollment in college.

Our original research question focused only on high school math course and remedial math enrollment, but once we started examining both the propensity score prediction models and the models employing propensity scores, we noticed some strong influences of our noncognitive attributes. So, we conducted additional analyses focusing explicitly on these variables.

We employed the same basic analytic strategy, but only used logistic regression, as propensity score weights are less appropriate for more innate variables like self-efficacy.

We focused on the association between three non-cognitive attributes, math self-efficacy, English self-efficacy, and extrinsic motivation, and their associations with remedial math enrollment. The self-efficacy scales measured students' beliefs in their abilities to be successful in math and English courses and the extrinsic motivation scale measured the extent to which students said they worked hard in school specifically to achieve goals like good jobs and financial security.

NCES derived these noncognitive attributes from students' responses to specific items on noncognitive assessments and scaled them to have a mean of 0 and standard deviation of 1

This graph shows the mean score on each cognitive attribute among students who did not enroll in remedial math (which are the dark blue bars) and students who did enroll in remedial math (which are the light blue bars). We see huge differences in scores on all three measures, with students who did not enroll in remedial math scoring well above average and students who enrolled in remedial math scoring below average. The biggest difference was in math self-efficacy.

This table presents the marginal effects for each noncognitive attribute after controlling for other factors. The first three rows are from the models for all college enrollees, the next are for four-year enrollees, and the last three rows are for two-year college enrollees.

We ran seven models for each sample, introducing a new set of control variables each time, but we only present the three major models here.

In the first column, we see strong significant associations between math self-efficacy and remedial math enrollment. For all enrollees, a one-point increase in math self-efficacy score is associated with an 8.2%

decrease in remedial math enrollment after controlling for other noncognitive attributes. This association was stronger for two-year college enrollees compared to four-year college enrollees. English self-efficacy and extrinsic motivation were not significantly associated with remedial math enrollment (after accounting for math self-efficacy).

The second column shows that the association between math self-efficacy and remedial math enrollment decreases with the introduction of measures of academic preparation such as HS GPA. But the association is still significant for all enrollees and for two-year enrollees. It is no longer significant for four-year enrollees.

The final column presents results for the full model with all control variables. The association between math self-efficacy and remedial math enrollment remains about the same after controlling for personal, family, and high school characteristics.

Given the large number of covariates included in these models, this suggests that math self-efficacy—students' confidence in their ability to succeed in math—plays a huge role in their readiness for college-level math.

Although we could not show all of our models here, we found similar associations between math self-efficacy and enrollment in any remedial course. Associations between English self-efficacy and enrollment in any remedial course were significant in some models, but only math self-efficacy was significant in all models.

Overall, our results suggested that completion of Algebra II alone was not a good measure of students' readiness for college-level math. Even completing a course above Algebra II was not a consistent measure of readiness. I will say that our models were quite sensitive to the specific covariates we used and to whether we used logistic regression alone or logistic regression with propensity score weights so this analysis should be considered preliminary. Even in a robust dataset like ELS, we may not have all the information we need to understand why course-taking is not strongly associated with college readiness in math.

Our results do suggest that a variety of student characteristics and experiences each play some role in remedial math enrollment. We found a particularly strong association between math self-efficacy and remedial enrollment. This suggests the potential value of interventions and messaging designed to strengthen students' self-confidence in math. We would also encourage future research into noncognitive attributes and various aspects of college-going and college success.

<u>4th Speaker</u>

Good afternoon. My name is Melinda Whitford. All the members of my group came into the data institute with a focus on STEM education, particularly in middle and high schools. Interestingly, we have very diverse backgrounds in our fields of study. My field is in math and science education, other group members are educational psychology and higher education, so we had quite a few different research questions that were proposed at the beginning. Through the development work that we did, the consensus of the group was too look at whether out-of-school time structure and unstructured STEM experiences influenced the students' aspiration in college.

This slide lists the team members along with our mentor, Karen Webber. She worked very closely with us and gave us great feedback. And as you can see, we do come from a variety of different institutions.

Here are the two questions that we pitched to the other groups during the Institute about why our study is interesting and has value. What makes STEM career interest more attractive to high school students and do high school math- and science-related curricular and extra-curricular activities impact on STEM aspirations in college major selection?

Again, from our developmental process, we designed three research questions. We are all mostly academic researchers and we really did approach our study through an academic research lens. So, the three research questions we developed are:

How are students' math-related curricular and extracurricular experiences related to their plan to major in STEM fields in college?

How are students' science-related curricular and extracurricular experiences related to their plan to major in STEM fields in college?

How do the aforementioned relationships vary by students' sociodemographic background?

The research questions ultimately did come from our study of the datasets that were available and since the HSLS:09 (High School Longitudinal Study) had a STEM component in their questions and variables, we used the publicly accessible data from the base-year and the first follow-up surveys, along with the high school transcript records.

Our theoretical framework is grounded in both social cognitive career theory by Lent, Brown, and Hackett and expectancy-vale theory of motivation by Wigfield and Eccles. Social cognitive theory posits that personal experiences and background, learning experiences, interest, self-efficacy and outcome expectations are factors related to actual career and academic choices.

Expectancy-value theory of motivation was originally designed to understand math achievement by highlighting the reciprocal relationship between the exposure to academic experiences and self-efficacy to shape students' motivation and goals. Since we posit that both math and science academic experiences are related to a students' plan to major in STEM fields in college, we felt that the expectancy-value theory could be extended to science achievement as well.

It is always important to find theoretical frameworks for your research, and we felt these two theories really fit our research study well.

Our group includes some individuals with advanced statistical analysis skills. When you undertake a research study, it is good to know who can do what. This can affect the types of research questions that you can develop and which datasets you use. Based on our research questions and dataset, we chose a probit regression analysis. The outcome variable is a dichotomous variable that represents whether the student responded that they had aspirations of enrolling in a STEM major in college or not. The predictor variables were categorized into blocks representing STEM experiences in high school, background academic characteristics, and background sociodemographic characteristics. And again, since we are using HSLS:09, we also used the analytic weights and the replicate BRR weights provided in the dataset.

What did we find? Well, students who use the internet to look up information about science or visit science museums frequently or who participated in science camp or science study groups are more likely to aspire to STEM fields in college. We also found that students who had higher math proficiency, higher self-efficacy in science, and higher high school cumulative GPA were also more likely to aspire to STEM fields. And, of course, being male is predictive of aspiring to a STEM field.

And well, most of you are probably thinking, yeah, that seems like common sense and I would agree. What is most interesting is that during the literature review phase, we couldn't find in the literature where any other researcher had actually studied STEM aspiration in college from an extra-curricular math/science lens. So, it really did add something new for us that we could continue to explore further.

At the end of the meeting in D.C., we were asked what possible next steps were that we could take to extend our research. At the end of the meeting, our group committed to continuing what we had been doing, with the exception of one us. The remaining five of us have kept in contact and we've continued to extend our work. The release of the second follow-up survey last summer and having one member apply for the license for the restricted dataset allowed us to modify the original analysis to a propensity score-adjusted probit path model. We've been working on this model since we got back to our home institutions. Hsun-Yu and Hyejin have taken the lead on the analysis and the research report. The intent after leaving D.C. was to submit conference proposals at AERA (American Educational Research Association) and NARST (National Association of Researchers in Science Teaching) and work on a research article journal submission.

The new methodology is a propensity score-adjusted probit path model. And of course, you're asking ... why? I'll just reiterate that three of us have some very advanced statistical skills and it's a challenge that is fun for us. It's a little crazy, I know. But, by doing this analysis, it essentially gives us a more robust model. It considers not only the complex sampling design, but it also allows us to address the self-selection bias of students' participation in STEM activities.

The first step was to do a confirmatory factor analysis to verify the hypothesized factor structure of the students' experience of participation in these activities. We were able to include the sampling strata, clusters and cross-sectional sampling weights. Once this was done, we completed a propensity score analysis and included the inverse propensity weights into the structural equation model.

This is a conceptual path model showing the hypothesized structure between the different factors, including the STEM experiences, students' aspirations to STEM in college, academic achievement, and self-efficacy constructs along with the socio-demographic background variables.

And this is the resulting path model with the significant path estimates. I'm not going to spend time going through each statistically significant path. If you're interested, you can come back to this slide later. I am going to go right to the updated results on the next slide.

So, what did we find? Basically, similar results. Students who participated in structured science activities before and during high school, who were more academically ready (in math and science), and who aspire to STEM fields in high school were more likely to enroll in a STEM degree program in their first year of college.

What impact could this have on STEM education? Hopefully, it will add to the discourse regarding how we need to continue encouraging students to consider STEM career fields. As a nation, we should be concerned at the lack of domestic students entering these fields. And, we should be bolstering our educational systems to engage students, and even more so, specifically engaging women and under-represented minorities to consider STEM degree programs.

Where has this led us? At the end of the D.C. meeting, one of the goals was to present our research at conferences. This past weekend, we presented at AERA (American Educational Research Association) in Toronto and the week before there was a poster presentation at NARST (National Association of Researchers in Science Teaching) in Baltimore. We will also be presenting at the AIR Forum in Denver at the end of May.

And, we are still working on writing a formal research article for journal submission.

Questions & Answers

Closing