The Influence of Labor Market Outcomes Data on Major Choice: Evidence from a Survey Experiment

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Abstract

The rising cost of college and demands for accountability have increased interest in providing students with information about the earnings of college graduates by school and major. However, no consensus exists over how to display that information in a way that is most beneficial for students. Some researchers advocate displaying median earnings only, while others advocate showing more detail on the variation in earnings. We argue that an explicit theory of student choice is missing from discussions about the provision of earnings data. We use a survey experiment to assess two models of student choice: one in which students use median earnings, and one in which students use median earnings and earnings variation. We demonstrate that showing respondents the median and variation leads to large and significantly different expectations in earnings and different choices in majors, compared to respondents who see the median only. The results question the use of medians only as a tool to improve student decision making. In contrast, displaying medians and variation provides influential information that allows students to make educational choices that incorporate risk.

1 Introduction

In the United States, it is widely believed that a college education is necessary to remain competitive in the modern economy. College graduates on average have higher lifetime earnings (Angrist and Chen 2011; Carnevale, Rose, and Cheah 2011; Oreopoulos and Petronijevic 2013) and lower unemployment rates compared to those with no college degree (Abel, Deitz, and Su 2014; Grusky, Red Bird, Rodriguez, and Wimer 2013). But with federal government estimates of student loan debt surpassing one trillion dollars (Chopra 2013), combined with diminishing employment prospects of college graduates (Abel et al. 2014; Stone, Van Horn, and Zukin 2012), there has been widespread interest in providing more information to consumers about the labor market outcomes from college (Jacobson and LaLonde 2013; Johnson, Majia, Ezekiel, and Zeiger 2013; Long 2010; Moore, Chapman, Huber, and Shors 2013; Mullin and Lebesch 2010; Owen and Sawhill 2013). The goal of this information is to improve the decision making regarding the colleges students attend and the majors they choose.

Despite the potential importance of labor market outcomes for student decision making, little is known about how this information influences those who use it. While all agree that the data shared with students must be relevant to the decisions they need to make, research has yet to identify the type of information that is most relevant for students making educational decisions.[3]

[3] The content of the information displayed differs from the form in which it is presented, its design, and how it is displayed, which also has important implications for how students process and act upon the information. The focus of this paper is exclusively on what to display to students, leaving the question of how to best display it to

Figuring out the optimal information to present to consumers is a challenge, because there are many quantities of interest, such as the mean, median, and inter-quartile range, that could be presented at varying levels of specificity for different sub-groups of students at different times after they have left college (Moore et al. 2013; Voight, Long, Huelsman, and Engle 2014). In this study, we examine the specific issue of the type of statistic to present on the labor market earnings of college majors: median earnings alone or the median combined with earnings variation.[4] Median earnings alone, or other measures of central tendency such as average earnings, conveys information in a simple manner on the most typical earnings outcome for a given major, while the average combined with variation conveys information on the full range of possible earnings, providing students with relevant information on the risk associated with a given major. The issue of whether to present information on the median or the variance is under debate among analysts involved in making these data more available to consumers (Hershbein and Hollenbeck 2014; Jacobson and LaLonde 2013).

To assess how the presentation of different types of earnings information influences student educational choices, we conduct a survey experiment with a national convenience sample of U.S. adults. The experiment allows us to manipulate the information respondents see and, through random assignment, eliminate the confounding influence of unobserved factors associated with treatment assignment and outcomes. We compare the effect of presenting median earnings with the effect of presenting the median plus the variation in earnings on educational choices. We find large and statistically significant differences across experimental groups. Compared with respondents who were shown only the median earnings, respondents who

future research.

[4] We use median throughout the paper for consistency and because the median is less sensetive than the average to the influence of individuals with extremely high and low earnings.

observed the variation in earnings were significantly more likely both to select the major with higher variation in earnings and to estimate a higher probability of earning above the median.

The paper proceeds as follows. In Section 1, we provide background on the policy context, review the related literature on earnings and major choice, and discuss our empirical expectations. In Section 2, we describe the experimental design of our study and use administrative data to compare different visual displays of earnings outcomes. Section 3 presents the results of the experiment, while the Section 4 discusses the findings. Section 5 concludes the paper.

1.1 Policy Context: The Push for Labor Market Outcomes Data

Despite rising costs, a college education remains a good investment (Abel, Deitz, and Su 2014). Yet, because of the rising costs of college, it has become increasingly important for students to make the right choices about where to attend college and what to study, leading to a national push to provide students with information, especially information on the outcomes of college graduates, to help them make better-informed educational choices. The push to offer information about college outcomes is perhaps best illustrated with the Obama Administration's College Scorecard. The College Scorecard aims to improve the transparency and accountability of higher education by providing financial information about the costs and outcomes associated with colleges so students "can choose a school that is affordable, best-suited to meet their needs, and consistent with their educational and career goals" (Obama Administration 2014). The College Scorecard seeks to provide employment information on graduates by college as part of its broader effort to provide information to guide consumer choice in higher education through the College Affordability and Transparency Center (Obama Administration 2014).

Likewise, several state-level efforts promote the availability of college outcomes data to consumers. State reporting systems make information from their institutions on student outcomes publically available, and many of these systems include labor market outcomes. For example, California's community college system developed a reporting system that makes employment outcomes data available to the public.[5] Likewise, Texas provides a vast amount of data on higher education outcomes on its gainful employment website.[6] Other states, including Florida, Minnesota, Virginia, and Washington, have data on median earnings available at the program level (Moore et al. 2013). While not yet available across all states, labor market outcomes data are becoming increasingly available nationwide, as many states receive federal funds to support the linkage of their Unemployment Insurance wage records with other state systems, including higher education (Jenkins and Harmon 2010; U.S. Department of Labor 2014).

Private and nonprofit organizations are also promoting the availability and use of labor market outcomes data in decision making. Two prominent efforts are the websites from CollegeMeasures.org and College Reality Check. CollegeMeasures.org provides information on college outcomes nationally, and has worked with several states, including Arkansas, Colorado, Florida, Tennessee, Texas, and Virginia, to assist them in making earnings data on their graduates publically available.[7] College Reality Check provides information on college outcomes nationwide to assist in decision making; this website uses earnings data from a company named PayScale to provide earnings information and prompt students to consider earnings by posing the

[5] See http://datamart.cccco.edu/Outcomes/System_Wage_Tracker.aspx. Last accessed September 4, 2014.
[6] See http://www.txhighereddata.org/reports/performance/ctcasalf/gainful.cfm. Last accessed September 4, 2014.
[7] See www.collegemeasures.org. Last accessed September 4, 2014.

question: “Will I make enough to repay my debt?,” and then showing information on earnings at starting and mid-career points.[8]

While these data inform multiple stakeholders, calls for increased availability of data have focused heavily on their use in informing consumer decision making.[9] Labor market outcomes data are primarily intended to inform the choice of which college to attend and which college major to select in order to eventually secure employment consistent with a student’s goals and expectations (Herndon 2012; Hershbein and Hollenbeck 2014; National College Access Network 2013; Owen and Sawhill 2013; Voight et al. 2014). Better labor market information may also improve chances of enrollment (Aspen Institute 2013; Morgan, Leenman, Todd, and Weeden 2013), as well as persistence in college (Aspen Institute 2013; Stuart, Rios-Aguilar, & Deil-Amen 2014).

Current efforts to provide labor market outcomes data present different statistics to summarize earnings information. Two positions about the display of earnings data are prominent in writings on student outcomes and labor market information. First, one widespread approach is to display the median earnings by major. For example, salary information that allows for the comparison of earnings across majors is available at websites like PayScale’s College Salary Report and in reports such as Carnevale and Cheah (2013).[10] When researchers present justifications for showing only the median, they argue that the median is a simple, easily

[8] See www.collegerealitycheck.com. Last accessed September 4, 2014.
[9] Data on the labor market outcomes are important to several stakeholder groups with different potential uses for the data. These groups include consumers (i.e., students and parents) who can use the data to guide their decision making, policymakers and the public who can use the data to assess the outcomes on public investments in education and adjust policy accordingly, and institutions that can use the data for performance improvement (Aspen Institute 2013; Voight, Long, Huelsman, and Engle 2014).

[10] See http://www.payscale.com/college-salary-report-2014. Last accessed September 4, 2014.

interpretable measure of the expected earnings in a major; additional statistics may overwhelm students by providing too much information (Baum, Kurose, and Ma 2013; Jacobson and LaLonde 2013; Schneider 2013).

Other analysts argue that variation in earnings in addition to the median provides useful information for students and should be provided (Moore et al. 2013; Mullin 2013). Advocates of this approach argue that students and parents can be misled about the expected earnings without knowing about the distribution of earnings (Hershbein and Hollenbeck 2014). Variation provides students with greater information about the nature of potential earnings across fields—some fields have a wide distribution of earnings and others have a more tight distribution of earnings. This information might enhance students' ability to predict their own potential future earnings and thus make better decisions about their major and/or student loan debt (Avery and Turner 2012).

Displaying the variation in earnings may encourage students to reflect on the personal characteristics that may influence their future earnings. Do they think that they have the ability to be a high performer in their selected field of study, or might they end up on the lower end of the earnings distribution? Will they be able to obtain employment in their field of study that has high earnings because of their knowledge and social connections in the field? Alternatively, some analysts have expressed concerns that the variation in earnings may misinform students as they may focus too much on the high end of the distribution and be overconfident in their eventual earnings (Hershbein and Hollenbeck 2014).

Ongoing efforts to make labor market outcomes data available represent attempts to provide information where students have traditionally had little to no information (Herndon

2012). Data on labor market outcomes have simply been less available for higher education than other outcomes such as completion of degree (Voight et al. 2014). As such, these data are being introduced into a low-information environment where they could potentially have significant impact on the students' knowledge of labor market outcomes. Although the magnitude of the potential effect is large, little is known about the impact of this information on students.

While efforts to make labor market outcomes data publically available to consumers continue to expand, knowledge of how the display of labor market information affects student decision making is still under development and in need of theoretical motivation. Rigorous testing based on theory-driven expectations will help clarify how the presentation of different statistics summarizing labor market information actually informs student choice.

1.2 Prior Research on Earnings Information and Decision Making

Our work builds on a considerable theoretical and empirical literature, primarily in economics, detailing the relationship between earnings and educational choices. Much of this work relates educational choice to expected future income of the major. Willis and Rosen (1979), for example, show in a widely cited study that U.S. veterans' predicted income significantly influences their decision to attend college. Warrick, Daniels, and Scott (2010) examine the association between expected income and preferences over public- and private-sector accounting careers. Other scholars have noted this same pattern; future expected earnings influence the decision to attend college, and the decision on what to choose as a major (Altonji, Blom, and Meghir 2012; Arcidiacono, Hotz, and Kang 2012). Research has also shown that earnings information influences both students' choices and subjective expectations about their earnings potential. In their survey of New York University undergraduate students, Wiswall and Zafar

(2013) find that students use earnings information to update their own expected earnings, and these revised earnings expectations influence major choice.

Beyond expected earnings associated with majors, information on the variation, or risk, in earnings associated with majors is another dimension to inform decision making. Education is an investment in human capital (Becker 1994), and knowing the risk associated with an investment is as important as its expected return. Making investment decisions without incorporating the riskiness of the investment is at odds with most financial theories of investment. Investment decisions in financial economics regularly incorporate expected earnings and risk.

Investment theory uses assumptions that investors optimize asset portfolios with mean and variance of their portfolios. One of the most influential models is the Markowitz mean/variance optimization analysis (Markowitz 1952). Under this framework, the investor seeks to maximize the expected return and standard deviation of return of the function $d = e - v/t$, where d is the investor's preference for the portfolio, e is the expected return, v is the variance of return, and t is the investor's risk tolerance. This simple model illustrates the role of variance and risk aversion in investment decisions. As v increases or t decreases, the preference for the portfolio decreases. It provides an intuitive representation of investment decisions. Educational choices are also investment decisions made under uncertainty. Yet, students often receive information that shows the expected return of educational choices. In other words, an assumption is made that students use an investment model of the following form $d = e$, instead of $d = e - v/t$.

Scholars have begun to explore how risk influences educational choices. In their review of educational decision making, Altonji, Bloom, and Meghir (2012) note that the variance of earnings—as a measure of risk—should be an important consideration for students when considering earnings information. Zocco (2009) studies risk in the context of student course selection. Using a sample of Danish students, Nielsen and Vissing-Jorgensen (2006) provide empirical evidence that students prefer educational choices for fields with high median earnings and low risk. Likewise, Attanasio and Kaumann (2012) find evidence that perceived risk of earnings, as measured by the variance of future earnings, influences the decision to attend college among poor Mexican youth. Moreover, they find that perceived risk is particularly important for the parents of students.

More recently, Wiswall and Zafar (2013), based on subjective assessments of the risk associated with given majors, find that students exhibit risk-averse behavior in the choice of majors. They assess risk by showing students the range of earnings by major. Information on risk may be particularly relevant to low-socioeconomic-status students, who are more likely to choose majors with less risky post-graduate earnings outcomes and often know less about the labor market (Betts 1996; Saks and Shore 2005).[11] Given this research showing the importance of risk in educational decision making, developers of educational scorecards must consider the effects of including risk when presenting information about post-graduate earnings.

In understanding how students make sense of earnings information, it is important to recognize that numerous factors can influence their expectations about future earnings, including a mix of private information (e.g., ability in a major) and public information (e.g., earnings data). Private information in the form of academic ability has an important relationship to major choice, occupational choice, and earnings expectations. High-ability individuals are attracted to the subject matter associated with higher-earning majors and high-earning jobs after graduation (Arcidiacono 2004). Greater performance, or academic achievement, reflects human capital acquisition and thus should be correlated with earnings; that is, we would expect students with

[11] Rouse (2004), however, finds no difference by socioeconomic status in knowledge of the labor market outcomes associated with different levels of education.

high academic achievement to have higher earnings than those with lower academic achievement (Becker 1994). Whether this knowledge is salient to students is not well known, though Wiswall and Zafar (2013) find a high correlation between students' self-assessments about ability and earnings expectations. When assessing information on the risk of a given major, through the variation in earnings, students' understanding of the relationship between academic achievement and earnings is of particular relevance, as we discuss in the following section.

1.3 Empirical Expectations

In this study, we assume that individuals update their expectations about future earnings when provided with accurate information about the earnings of graduates, as found by Wiswall and Zafar (2013). We then investigate how different types of information affect earnings expectations and decision making with regard to the choice of major. Using the findings from the above discussion of theoretical and empirical work, we form two empirical expectations for our experiment:

1. Earnings information that includes variation leads to different educational choices compared to earnings information that includes median earnings alone.
2. Earnings information that includes earnings variation leads to different expectations about earnings compared to earnings information that includes the median only.

The first expectation denotes that we expect to find differences in the choice of major between those who see the median and variation and those who see the median only. The differences in choice arise because of differences in earnings expectations between the two groups. The second expectation denotes that we expect to find differences in the earnings expectations between those who see median and variation and those who see the median only. The difference arises due to varying risk preferences, decision making biases, and private information.

We now present a third empirical expectation:

3. High-academic performers are more likely to choose the high variation major compared to low-academic performers

The third expectation is intended to assess how private information about a student's academic ability influences the use and interpretation of labor market outcomes data. In particular, we expect that high academic ability students will be more likely to form earnings expectations toward the high end of the earnings distribution. In contrast, low academic ability students will be more likely to form earnings expectations near the bottom end of the earnings distribution. The high academic ability student is then more likely to choose the high variation major, since that choice offers greater potential earnings than the low variation major. Meanwhile, the low academic ability student is more likely to choose the low variation major, since that choice offers less potential risk of achieving a low-earnings outcome.

2 Data and Experimental Design

We conducted a survey experiment in which individuals are randomly chosen to view different information about labor market outcomes. The survey begins by asking respondents to read a vignette about a fictional college-bound student, Steve.[12] Respondents read about Steve's academic background and interests, and then view earnings outcome information about two

[12] We choose a traditionally male name rather than a traditionally female name in order to focus on the effect of labor market information. Using a female name may prime respondents to consider perceived and real gender biases in risk aversion, labor market outcomes, and academic performance. These are interesting and important considerations for future work.

college majors that we chose to highlight differences in the variation in earnings. After viewing the earnings outcomes, respondents are asked to make estimates about Steve's post-graduate earnings and recommend which major Steve should choose. This vignette approach to survey research is a common method used to approximate decision making within a heterogeneous respondent population (Alexander and Becker 1978; Mutz 2011).

We ask respondents to recommend the major for Steve, rather than report their own preferences about majors, in order to allow us to isolate how earnings information affects the choice of major. In particular, there is a high degree of heterogeneity across respondents in tastes, academic ability, and private information about their own labor market prospects. Although randomization of the treatment guarantees that, on average, these traits will be balanced across the treatment and control groups, they introduce considerable variance into the estimates of treatment effects. Therefore, we ask respondents to instead focus on a fictional character, for whom we can control these characteristics. Although the answers apply to a fictional character, we still are able to assess how labor market information affects the evaluation of different majors.[13] Question wording was decided only after conducting pre-tests with Rutgers University students.

To recruit a sample of respondents, we used Amazon's Mechanical Turk (MTurk). MTurk is a platform for hiring people to work on computer-based tasks and is increasingly used to field social science experiments.[14] Our study is limited to U.S. adults and restricted to respondents with MTurk approval rates above 98%, which is an indicator of a respondent's reputation for

[13] Wiswall and Zafar (2013) employ a within-subject design to control for individual preferences. Our survey budget made this more time-intensive design infeasible.

[14] Berinsky, Huber, and Lenz (2012) find that MTurk respondents generally replicate experimental results obtained from other convenience samples, such as college undergraduates.

quality work. Before obtaining consent, we cautioned respondents that we would not compensate them for survey responses that were completed too quickly to be reliable (e.g., surveys completed in less than 30 seconds). We also stated that any respondent would only be allowed to take the survey once (each respondent leaves a unique IP address). After giving consent, a link directed respondents to the online survey, which is hosted by Qualtrics. Respondents received a payment of 75 cents for completion of the survey. A total of 601 respondents completed the survey, with an average completion time of 6 minutes and 10 seconds. We remove 12 respondents from the final dataset who either finished the survey in too short a time to have fully read the survey instrument or were registered by Qualtrics to have taken the survey more than once.

The sample characteristics deviate from national population characteristics, but reflect deviations commonly found in both adult and student convenience samples.[15] The median age of respondents is 28, with first and third quartiles equal to 24 and 34, respectively. Nearly 47% of respondents hold at least a college degree, and only 35% are female.[16]

One concern about this design is that by surveying adults we are missing how *students* evaluate labor market information. We agree that students are a crucial consumer of labor market information, and ongoing projects are assessing the effects of labor market information on a student sample. But adults are also consumers of labor market outcomes data. In fact, outcomes data are frequently marketed to parents and college-bound students. Parents have an incentive to use outcomes data when recommending majors to their children, particularly since the parents often finance all or part of a college degree. Adults, more generally, use outcomes data when

[15] See Berinsky, Huber, and Lenz (2012) for characteristics of frequently used convenience samples.
[16] Median age of U.S population is 37 according to the 2012 U.S. Census. The 2012 American Community Survey reports that 28.5% of the population holds a college degree.

deciding whether to return to school and choosing a program of study. For these reasons, studying how a sample of U.S. adults evaluates this information is of substantive interest in itself.

One other concern involves the external validity of an experiment conducted on the MTurk non-probability sample. External validity requires us to consider to which population the experimental results generalize. Our convenience sample, as stated above, is more educated, younger, and male than the U.S. population as a whole. However, our primary goal in this paper is to estimate a causal relationship between earnings information and educational choice. Achieving that goal requires careful design of the experiment and randomization of the treatment among the respondents. In this analysis, we are not estimating the effect of earnings information on a given population, such as U.S. adults with children, or U.S. college-bound students. Understanding how these estimated effects generalize to different populations is a goal of future research.

The survey instrument is based on a 2x2 factorial experimental design. The factorial design is defined as an experiment with two or more factors, in which respondents are randomly assigned to each possible experimental condition (Gerber and Green 2012). Its particular advantage is that it allows us to examine how the treatment effect (which labor market earnings information is displayed) changes depending on the values of the second factor (the achievement condition).

The primary experimental factor involves the display of earnings information. The control condition for earnings information, which provides information on average earnings alone, is shown in Table 1. The treatment condition for earnings information, which provides information on average and the variation, or risk, in earnings, is shown in Table 2 and Figure 1. We present data on two majors only: mathematics and economics. We choose these two majors because a quantitatively oriented student could reasonably choose either major, so our vignette contains a plausible choice for our fictional Steve. Second, the two majors have similar median earnings but much different variation in earnings. Economics with its wide earnings dispersion is a more risky major, whereas mathematics with its more narrow earnings distribution is a less risky major. Thus, the two majors provide an ideal test for the influence of showing the variation in earnings versus the median alone.[17] Respondents who are in the control group see the same table, but we show the median only.[18] We show the treatment condition for earnings data in both a table and a figure to make the data easier for respondents to interpret. In the data presented to respondents, we label median earnings as average earnings to simplify the understanding of this measure for respondents as a measure of central tendency, since average is more widely understood than median. Our calculations reveal very little difference between median and mean.

The data presented in the tables and figure is calculated from New Jersey administrative data under the Workforce Data Quality Initiative. We link student enrollment records from New Jersey public universities and colleges to Unemployment Insurance wage records, which include nearly all graduates who work in New Jersey. We use New Jersey data, rather than national data, in order to provide more contextualized information about the possible earnings outcomes for Steve as is increasingly being done in states around the nation. In the survey instrument, we ask respondents to consider that these are earnings in Steve's state, where he plans to live and work.

[17] Of course, not all majors have comparisons this stark, which raises the concern that differences are not common and thus not of much importance. However, our concern is this paper is to show whether these differences can have an impact on student choice. For this reason, we choose two majors where variation in wages could lead to different student choices.

[18] We indicate that wages are for graduates near age 30 so respondents don't lower expectations based on the time after graduation needed to find a job or attendance in graduate school.

Thus, state-level earnings are a more accurate projection of labor market outcomes than national earnings.

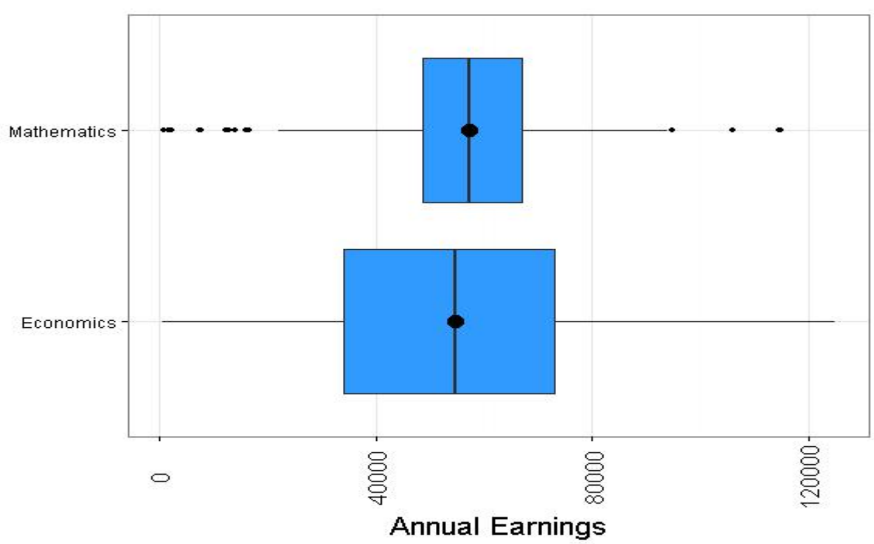
Table 1: Control condition for earnings information

Major Category	Average Earnings
Mathematics	$57,000
Economics	$55,000

Table 2: Treatment condition for earnings information

Major Category	25% Make Less Than	Average Earnings	25% Make More Than
Mathematics	$49,000	$57,000	$67,000
Economics	$34,000	$55,000	$73,000

Fig. 1: Visual display of data for the treatment condition for earnings information



The secondary experimental factor is the *achievement* condition. We introduce this second factor by randomly assigning respondents to one of two prompts, which respondents read before proceeding to the earnings information. The prompts introduce information that can influence Steve's propensity to realize higher earnings in the labor market. Specifically, we mention Steve's academic ability, since many studies have shown that academic and cognitive ability influences labor market outcomes (e.g., Cawley, Heckman, and Vytlacil 2001).[19] We introduce this information in order to hold constant Steve's private information about his prospects for success in the labor market as we vary the information we provide about earnings. We then are able to assess whether private information about labor market prospects influences the interpretation of earnings data.

Two levels of the achievement factors—high and low—are shown below. In addition to the private information, we also include other information that holds constant factors related to major choice and earnings. In our experiment, we aim to highlight the influence of earnings information on major choice, and not school of graduation or preference for one major over the other. Thus, in each condition, we state that Steve is at a large public university, is choosing between two majors, and is likely to perform equally well in each major. This information is intended to hold schooling and academic ability constant within each condition, so that the respondent does not recommend one major over another due to perceived opportunities available to graduates of elite schools or perceived chances of academic success. The last piece of information we provide is on the amount of student loan debt Steve will have. We hold this constant in all scenarios but include this information as a primer that earnings after college will be important for Steve.

[19] While we also recgonize that other factors, such as social and family connections, are important, we do not examine these in this experiment because of limitations in scope of the study.

High Achievement: Steve is a sophomore at a large public university and is trying to decide on a major. He is choosing between mathematics and economics. He has always been a high achiever academically, and expects to perform equally well in each major. He will graduate with approximately $30,000 in student loans.

Low Achievement: Steve is a sophomore at a large public university and is trying to decide on a major. He is choosing between mathematics and economics. He has always struggled somewhat academically, and expects to perform equally well in each major. He will graduate with approximately $30,000 in student loans.

After we randomly assign individuals either to the *high academic achievement* condition or to the *low academic achievement* condition, we then randomly assign respondents into one of two conditions in the earnings information factor. In the first condition, which we call the *low information* condition, respondents view only the median earnings for both economics and mathematics. In the second condition, which we call the *high information* condition, respondents view the median earnings and the first and third quartiles of the earnings distribution for both economics and mathematics.[20] The first and third quartiles summarize the spread of the distribution, capturing the variation in earnings. Our experiment thus has four experimental conditions: *high information* and *high academic achievement*, *high information* and *low academic achievement*, *low information* and *high academic achievement*, and *low information* and *low academic achievement*.

Each experimental condition is designed to assess our theoretical expectations described above. In particular, *high information* gives respondents accurate information about the

[20] In the survey instrument, we use the term "average" instead of "median" in order to avoid any possible confusion among respondents unfamiliar with the term "median."

distribution, or risk, of earnings by major. Risk information allows respondents to choose a major consistent with their risk preferences. In contrast, the *low information* condition forces respondents to recommend a major based on their own and often inaccurate estimate of the true risk associated with the major. The recommendation of major based on erroneous estimates of risk leads to respondents selecting majors that are inconsistent with their risk preferences. Across both high and low information treatments, we randomize respondents by the high and low academic achievement conditions. By randomly varying levels of academic achievement, we assess whether high (low) academic achievement induces more (less) acceptance of the risk associated with a major's labor market outcomes.

After viewing the labor market information in the experimental conditions, respondents report how much Steve is likely to earn in a given major, how likely Steve is to earn above \$70,000 per year, how likely Steve is to earn below \$38,000 per year, and whether they recommend that Steve pursue a given major. The first question assesses expected earnings in the major, while the second and third questions assess the risk associated with the major, in the form of high or low earnings, and the final question involves the educational choice of the respondent.[21] The full survey instrument is available in the appendix.

We conduct randomization checks and find evidence that the randomization of information and ability treatments were successful. Across experimental conditions, we find no significant difference in the observable variables of gender, age, or education. In the treatment group, we find a slightly greater percentage of female respondents, but the difference is not

[21] We choose the values \$70,000 and \$38,000 to represent typical high and low earnings outcomes for college graduates, based on the first and third quantiles of all graduates in our New Jersey administrative data.

statistically significant. When we include gender in the regressions presented below, we find substantively and statistically similar estimates.

In our analysis, we focus on estimating the sample average treatment effect (SATE), or the average effect conditional on our sample of respondents.[22] Since we randomly assign the treatment to respondents, a simple difference-in-means estimator is an unbiased estimate of the SATE. However, to simplify presentation of results and to maintain a unified estimation strategy throughout the paper, we use simple linear regression to estimate the SATE. More specifically, we use the linear probability model to estimate the treatment effect of labor market outcomes information on major recommendation. Since the dependent variable is dichotomous, an alternative strategy is to use logit or probit regression. We instead use the linear probability model since it allows for easier and more direct interpretation of the estimates, while still being a consistent estimator of the SATE (Angrist and Pischke 2009). Moreover, simple linear regression of the outcome on an indicator, or dummy, variable for treatment assignment is equal to the estimate of the difference-in-means estimator (Wooldridge 2002).

We also use the 2x2 factorial design to estimate the SATE given high or low levels of academic achievement. To estimate this SATE, we again use linear regression, including a dummy variable for high academic achievement and the interaction of high academic achievement and information treatment status. This regression exactly reproduces difference-in-means estimates from a 2x2 table of means by information treatment status and academic

[22] We focus on the sample, rather than the population average treatment effect, since our sample is a convenience sample and cannot be considered a representative sample from the population of U.S. adults. See Imbens (2004) for a discussion of the distinctions between the two estimands.

achievement level. Significance tests for estimates are based on large-sample approximations of the normal distribution and heteroskedasticity-robust standard errors.[23]

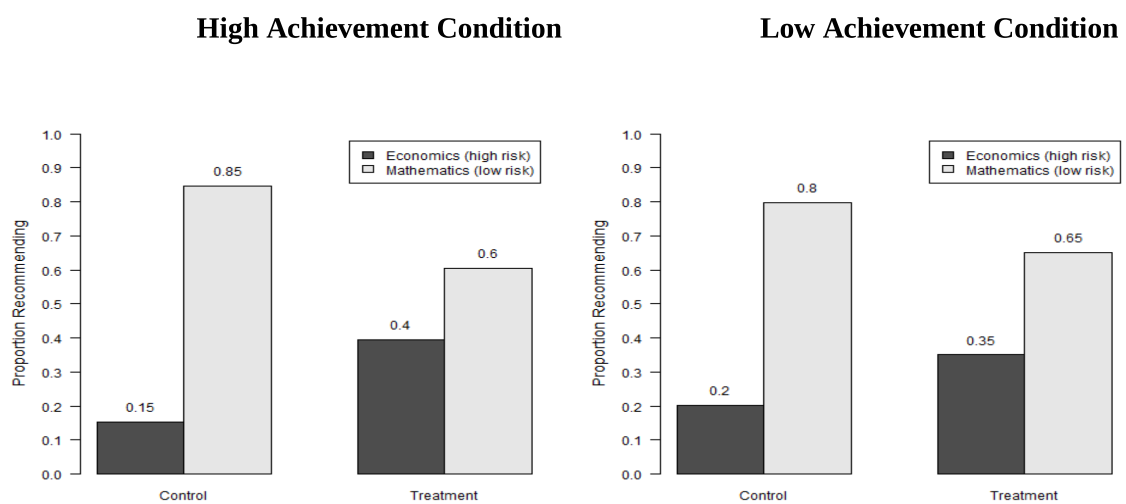
3 Results

3.1 Recommendation of Major

We begin by showing a visual summary of the responses. Figure 2 displays the proportion of respondents who recommended mathematics and economics, by achievement condition. The figure reveals a stark contrast between treatment and control conditions in both achievement levels. The respondents who view the median earnings only are much more likely to recommend mathematics. In the left panel, only 15% of respondents who see the median earnings recommend economics, the riskier major. The proportion is slightly higher in the right panel, where only 20% of respondents recommend economics, the riskier major. The respondents who view both the median earnings and the variation in earnings exhibit a much different pattern of major recommendation. In the left panel, nearly 40% of respondents recommend economics, which is a 25 percentage point difference from the control condition. What is surprising is that the right panel shows a similar pattern, meaning that even for the low achievement condition, in which Steve may be more likely to earn below the median, respondents are selecting economics at a higher rate than the control group. We return to discuss this finding at the end of this section.

[23] Researchers debate the use of large-sample approximations versus randomization procedures for statistical inference with experimental data (see Freedman (2008)]; Green (2009)]). Samii and Aronow (2012) show that the ordinary least squares variance estimate is equal to Neyman's conservative randomization-based variance estimate and the constant effects randomization variance estimate when the size of treatment and control groups is the same. When sample sizes are different, and treatment effects are assumed constant, heteroskedasticity-robust standard errors are equal to Neyman's randomization-based estimate.

Fig. 2: Proportion of responses in each experimental condition



We now report estimates of the SATE. Table 3 shows the estimates from two regressions. The *Treatment Only* column reports the estimated SATE of -0.192, which is simply the coefficient on the Treatment indicator. In other words, the treatment effect of showing variation in earnings causes a 19 percentage point decrease in the probability of choosing mathematics, the less risky major. The regression estimates in the column *Treatment by Achievement Levels* analyze whether the treatment effect differs significantly between the high and low achievement. Since the Achievement variable is coded 1 for the high-achievement condition, the coefficient on Treatment indicates that for the low achievement condition, respondents were 14.7 percentage points less likely to choose math than the control group. The coefficient on the interaction between *Treatment* and *Achievement* is the estimated difference in treatment effect between the high and low achievement groups. The estimate shows that the treatment group that saw the high achievement condition were less likely to select math (9.5 percentage points) than the treatment group presented with the low achievement condition,

While the estimate for the interaction effect is in the right direction, it is not statistically significant at the 0.05 level. We also use an F-test to test the null hypothesis that the coefficient on Treatment × Achievement is equal to 0. The result from the F-test, which also fails to reject the null hypothesis, is reported in the lower section of Table 3. A summary of estimated treatment effects is reported in Table 4.

Table 3: OLS estimates of linear probability models

	Treatment Only	Treatment by Achievement Levels
Intercept	0.823^{***}	0.797^{***}
	(0.022)	(0.033)
Treatment	-0.192^{***}	-0.147^{**}
	(0.036)	(0.050)
Achievement		0.044
		(0.043)
Treatment x Achievement		−0.095
		(0.073)
F-statistic for H_0: no interaction		1.74
p-value of F-statistic		0.187
Observations	589	589

$^{***}p<0.001$, $^{**}p<0.01$, $^{*}p<0.05$

Note: Dependent variable in each regression is equal to one if respondent recommended mathematics and zero otherwise.

Table 4: Summary of average treatment effects

Treatment Effect	Estimate

SATE (High Achievement)	-25%
SATE (Low Achievement)	-15%
SATE	-19%

Note: The SATE is statistically significant at the 0.01 level. The F-Test reported in Table 3 fails to reject the null hypothesis that the average treatment effect does not differ between the high and low achievement groups (F = 1.74, $p = 0.19$).

3.2 Information and Earnings Expectations

A key component of the theories of student choice outlined in Section 1.3 is that individuals base their major choice on their expectations of future earnings. Using those theories to develop empirical expectations, we suggest that the treatment induces a higher probability of choosing economics through its effect on higher earnings expectations. In other words, earnings expectations are the mechanism through which the treatment affects the outcome of major recommendation. An observable implication of this theory is that the treatment has a causal effect on earnings expectations.[24] While we do not claim to estimate the full causal chain—from treatment through earnings expectations to major recommendation—showing an effect of treatment on earnings is highly suggestive evidence in support of the theoretical expectations. Moreover, a finding of no treatment effect on earnings expectations would cast doubt on the theoretical expectations with regard to earnings uncertainty, and on the experimental manipulation itself.

We use the three regressions to estimate the SATE of variation in earnings on earnings expectations. The dependent variable in these regressions is a relative measure of earnings expectations. For example, in column two in Figure 5, we take the percent chance of making over

[24] In this analysis, we do not perform statistical mediation analysis. The methodological challenges faced in causal mediation analysis are discussed in Gelman and Hill (2006), Gerber and Green (2012), and Imai, Keale, Tingley, and Yanomoto (2011).

$70,000 in economics minus the percent chance of earning over $70,000 in mathematics. The relative measure captures the idea that being more likely to achieve higher earnings in economics causes respondents to favor that major, relative to mathematics. Positive values of the variable represent respondents who expect to earn more in economics than in mathematics, while negative values represent respondents who expect to earn more in mathematics than in economics.[25] In column four in Table 5, we calculate the difference in expected average earnings between economics and mathematics. Together, the three measures capture the treatment's effect on expected average earnings (column 4) and risk (columns 2 and 3). In other words, each measure corresponds to a different aspect of the theory of student choice: how likely the student is to obtain a high-earnings outcome, how likely Steve is to obtain a low-earnings outcome, and how much money the respondent believes Steve is most likely to earn.

We report the results from all three regressions in Table 5. We find that the treatment effect has a positive and statistically significant effect on the relative percent chance of high or low earnings. Showing respondents the variation in earnings causes nearly a six percentage point (5.91) increase in the difference between economics and mathematics among the low achievement group. The low achievement group that received the treatment was also more likely (7.00 percentage points) to report earnings for Steve below $38,000, compared to the low achievement group that viewed average earnings alone.

For the high achievement group, respondents were somewhat more likely (1.14 percentage points) to report that Steve will earn above $70,000, though this difference is not

[25] We also conducted these regressions using the probability of high or low earnings for each major alone; that is, we did not create a relative measure of earnings expectations. The treatment effect is large and statistically significant. However, we do not report these results since they cannot account for the relative preference of one major over another.

statistically significant. Respondents in the high achievement group were also somewhat less likely (-1.13 percentage points) to report that Steve will earn under $38,000, though again this difference is not statistically significant. The null finding with regard to academic achievement is consistent with our analysis of major choice, where we also find estimates in a direction consistent with the empirical expectation but not statistically significant different across achievement levels in the choice of economics and mathematics.

Respondents in the treatment condition, in other words, expected higher earnings in economics relative to mathematics. Similarly, respondents in the treatment group also expressed a greater chance of earning *less* in economics: the difference between treatment and control groups is seven percentage points.

Table 5: Ordinary least squares estimates of treatment and achievement level

	Relative % Chance Earning over $70,000	Relative % Chance Earning under $38,000	Expected Earnings (average)
Intercept	−1.46	−0.18	-2355
	(0.94)	(0.87)	(556)
Treatment	5.91***	7.00***	-879
	(1.19)	(1.39)	(-738)
Achievement	0.42	0.63	720
	(1.32)	(1.15)	(875)
Treatment x Achievement	1.14	−1.13	109
	(1.85)	(1.79)	(1214)
Observations	589	589	589
F statistic for nested models	0.39	0.38	0.008
p-value of F statistic	0.53	0.54	0.93

$^{***}p<0.001$, $^{**}p<0.01$, $^{*}p<0.05$

Note: Dependent variable in second column is the percent chance earning over $70,000 in economics minus the percent chance earning over $70,000 in mathematics. Dependent variable in third column is the percent chance earning under $38,000 in economics minus the percent chance earning under $38,000 in mathematics. Larger values indicate respondent estimates of greater variation in earnings for economics, relative to mathematics. The dependent variable in the fourth column is the difference in expected average earnings between economics and mathematics.

Treatment group respondents' estimates of a greater chance of high *and* low earnings reflect the higher variation of earnings in economics; respondents are reporting expectations that are consistent with the data. The control group responses provide a stark contrast. In the control group, respondents report almost no difference between the two majors. In column two, the control group average response is only a difference of -1.46 percentage points; in column 3, the control group average response is only -0.18. These small differences are evidence that respondents have poor estimates of the true variation in earnings in these majors. In particular, these small differences are consistent with respondents estimating similar variation in earnings across the two majors, while the real variation in earnings differs considerably.

The results, taken together, support the theoretical expectation that the treatment influences major choice through its effect on earnings expectations. Respondents use the information about variation to estimate probabilities over high and low future earnings outcomes. The treatment effect of information on major recommendation appears to be driven by the treatment causing respondents to estimate higher probabilities of earning high and low earnings, and not driven by changes in expected earnings. We find no evidence that the treatment effect is driven by changes in expected earnings: in column three, the coefficient on the treatment is small (-$878) and statistically indistinguishable from zero.

4 Discussion

In Section 1, we use economic theories of student educational choice to form three empirical expectations. Our first empirical expectation concerns the recommendation of major. Based on the theoretical and empirical work discussed in Section 1, we expect information about earnings variation to change, on average, the recommendation of major *through its effect* on earnings expectations. While we cannot identify this complete causal chain—from treatment to earnings expectations and major choice—with our experimental design (see Imai, Keele, Tingley, and Yamamoto 2011), we do report findings consistent with our expectation and the theories cited in Section 1.

Our second empirical expectation was that providing individuals with information about the variation in earnings leads to different earnings expectations compared to individuals who see median earnings alone. We find strong evidence in support of this expectation. Respondents observed the high variation in earnings for economics and used that information to report both a higher percent chance of earning more than $70,000 and a higher percent chance of earning less than $38,000. In other words, the treatment induces both more optimistic and pessimistic expectations about earnings.

We find no difference with regard to changes in average expected earnings. Respondents in both experimental groups are highly likely to choose at or near the median when asked to report how much Steve is likely to earn. We find no evidence that respondents use information about the variation in earnings to update the expected, or most likely, earnings amount.

This response pattern is consistent with individuals using earnings data to update their own erroneous prior beliefs about population earnings (Wiswall and Zafar 2013). Respondents in the control condition did not see the distribution in earnings and thus used their own prior beliefs to guess about the probability of achieving earnings above $70,000 and below $38,000. These prior beliefs appear to have been based on underestimated estimates of the variation of earnings in economics.

Our third empirical expectation concerns the role of academic achievement as a mechanism to explain why the interpretation of earnings data varies across individuals in our experiment. We find limited evidence of an effect for information about academic ability. In both the analysis of major choice and earnings expectations, the estimated differences in responses across academic achievement conditions were in the direction consistent with the empirical expectations but statistically insignificant at conventional levels.

Given research on the relationships between academic ability, major choice, and labor market outcomes (Arcidiacono 2004), we are surprised to not find strong evidence that respondents use information about academic ability to estimate future labor market outcomes. This null finding can be a result of several factors. Respondents may not believe there is a strong linkage between academic performance and post-graduate earnings. Respondents may also be influenced by optimism bias, discounting negative outcomes in both high and low academic achievement conditions. Finally, our academic achievement treatment may not be strong enough to cause respondents to believe that Steve's academic performance will affect his post-graduate earnings. Our treatment states that Steve "struggled somewhat" academically. Respondents possibly don't consider "struggled somewhat" to influence post-graduate earnings as much as, for example, a treatment that stated Steve was a significant poor performer in school.

The statistically significant treatment effects we report are average differences. Though the treatment effect of earnings information on major choice is quite large, the majority of respondents continue to choose mathematics in the treatment condition. Why, despite the promise of higher earnings in economics, do a majority of respondents recommend the less-risky major with less potential for higher earnings? It is likely that other mechanisms involved in respondents' interpretation of the earnings data explain this variation in responses. These other mechanisms include class-based factors such as social networks and/or economic resources, as well as or psychological traits such as risk-aversion and decision making biases. Our results are consistent with both risk-aversion and decision making biases influencing the earnings expectations and major choice. Risk-averse respondents recommend mathematics given the disutility of the low-earnings outcome in economics, while respondents influenced by optimism bias discount the higher probability of a low-earnings outcome in economics; respondents who do not discount the higher probability of the low-earnings outcome choose mathematics.

Our results are consistent with previous work analyzing risk and educational choice (Nielsen and Vissing-Jorgensen 2006; Wiswall and Zafar 2013). Overall, respondents in our sample prefer the major with less risk—mathematics. However, we show that a significant number of respondents prefer the high-risk major of economics when exposed to the variation treatment. This result shows that not all respondents prefer high-mean, low-risk majors. Rather, some respondents, possibly those with risk-seeking preferences or optimism bias, prefer the major with high risk.

Finally, our data provide limited information on the role of class-based factors. Our preliminary analyses of respondents of different class backgrounds suggest that the results vary by social class, when class is measured by parents' educational attainment. Future work should identify exactly how social class influences choice in the context of labor market information using more encompassing measures of social class.

5 Conclusion

Incorporating a simple model of student choice under uncertainty reveals some puzzling implications about common methods used to display outcomes data. Specifically, showing students the median only assumes a model of student choice in which students make decisions based on the future expected earnings only, ignoring the risk, or variance, of future earnings. This model of student decision making is equivalent to a model of investor decision making in which investors optimize their portfolio earnings without regard to risk preferences or the riskiness of the assets. We believe that the results in this paper show that an explicit theory of student choice is missing from discussions about the provision of labor market outcomes data. This is surprising, given extensive work in the social sciences documenting how expected earnings influence educational choices (Arcidiacono 2004; Arcidiacono et al. 2012; Becker 1994; Willis and Rosen 1979; Wiswall and Zafar 2013). One contribution of our experiment is a better understanding of the effects of omitting information on risk from scorecards, which presumes the mean-only model of student choice.

Based on the findings from this research, it is clear that information on the variation in earnings is an influential piece of information in the decision making process. Further research on this specific issue needs to be conducted with direct consumers of this information, including college students, their parents, and counselors who advise students and parents. In addition, given the potentially important role that information on risk as represented by variation in earnings has on low-SES students, further study specifically focused on these students is especially important. This future research may most effectively be conducted by examining the use of these tools in practice, including more in-depth understanding of how consumers react to these data.

Beyond the specific issue of whether to present earnings data as a median or a range, many other important decisions related to how these data are presented need attention. These decisions include the timing of the data relative to graduation, whether to provide the employment rate after graduation, which sub-group of students to report on, whether to report the data by college or program level, and whether to report on all students, including both graduates and non-graduates (Harmon, Ridley, and Zinn 2014; Moore et al. 2013; Voight et al. 2014).

Targeted research using experimental studies can shed light on these decisions around how to present data. Broader research on students' decision making processes and how these data inform their decisions (or not) is essential to help guide the development of useful and relevant data products. To achieve the goal of more informed decision making through better information rests entirely on ensuring the quality of that information. Further research can ensure that quality information achieves this goal.

References

Abel, J. R., Deitz, R., & Su, Y. (2014). Are Recent College Graduates Finding Good Jobs? *Current Issues in Economics and Finance/Federal Reserve Bank of New York*, *20*(1).

Alexander, C. S., & Becker, H. J. (1978). The Use of Vignettes in Survey Research. *Public Opinion Quarterly*, *42(1)*, 93–104.

Altonji, J. G., Blom, E., & Meghir, C. (2012). *Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers* (Working Paper No. 17985). National Bureau of Economic Research.

Angrist, J. D., & Chen, S. H. (2011). Schooling and the Vietnam-Era GI Bill: Evidence from the Draft Lottery. *American Economic Journal: Applied Economics*, *3(2)*, 96–118.

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly Harmless Econometrics*. Princeton University Press: Princeton, NJ.

Arcidiacono, P. (2004). Ability Sorting and the Return to College Major. *Journal of Econometrics*, *121(1-2)*, 343–375.

Arcidiacono, P., Hotz, J., & Kang, S. (2012). Modeling College Major Choice Using Elicited Measures of Expectations and Counterfactuals. *Journal of Econometrics*, *166(1)*, 3–16.

Aspen Institute. (2013). *A Guide for Using Labor Market Data to Improve Student Success*. Washington D.C.: The Aspen Institute.

Attanasio, O. P., & Kaumann, K. M. (2012). Educational Choices and Returns on the Labour and Marriage Markets: Subjective Expectations, Gender and Decision Making. *Unpublished Manuscript*.

Avery, C., & Turner, S. (2012). Student Loans: Do College Students Borrow Too Much—Or Not Enough? *Journal of Economic Perspectives*, *26*(1), 165–192.

Baum, S., Kurose, C., & Ma, J. (2013). *How College Shapes Lives: Understanding the Issues*. College Board. Trends in Higher Education Series.

Becker, G. S. (1994). *Human Capital* (3rd ed.). University of Chicago Press, Chicago.

Berinsky, A. J., Huber, G. A., & Lenz, G. S. (2012). Evaluating Online Labor markets for Experimental research: Amazon.com's Mechanical Turk. *Political Analysis*, *20*, 351–368.

Betts, J. R. (1996). What Do Students Know about Wages? Evidence from a Survey of Undergraduates. *The Journal of Human Resources*, *31*(1), 27–56.

Carnevale, A. P., & Cheah, B. (2013). *Hard Times: College Majors, Unemployment and Earnings*. Center on Education and the Workforce, Georgetown University.

Carnevale, A. P., Rose, S. J., & Cheah, B. (2011). *The College Payoff: Education, Occupations, Lifetime Earnings*. Center on Education and the Workforce, Georgetown University.

Cawley, J., Heckman, J., & Vytlacil, E. (2001). Three Observations on Wages and Measured Cognitive Ability. *Labour Economics*, *8(4)*, 419–442.

Chopra, R. (2013, July 17). Student Debt Swells, Federal Loans Top a Trillion. Retrieved from Consumer Financial Protection Bureau Newsroom at http://www.consumerfinance.gov/newsroom/student-debt-swells-federal-loans-now-top-a-trillion/

Freedman, D. A. (2008). On Regression Adjustments to Experimental Data. *Advances in Applied Mathematics*, *40*, 180–193.

Gelman, A., & Hill, J. (2006). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge University Press: New York, NY.

Gerber, A. S., & Green, D. P. (2012). *Field Experiments*. W.W. Norton: New York, NY.

Grusky, D., Red Bird, B., Rodriguez, N., & Wimer, C. (2013). *How Much Protection Does a College Degree Afford? The Impact of the Recession on recent College Graduates*. Washington D.C.: Pew Charitable Trusts, Economic Mobility Project.

Harmon, T., Ridley, N., & Zinn, R. (2014). *Workforce Results Matter: The Critical Role of Employment Outcome Data in Improving Transparency of Postsecondary Education and Training*. Washington D.C.: Center for Law and Social Policy.

Herndon, M. C. (2012). Improving Consumer Information for Higher Education Planning. *New Directions for Institutional Research*, *2012*(153), 63–74.

Hershbein, B. J., & Hollenbeck, K. (2014). *College Costs: Students Can't Afford Not to Know*. Kalamazoo, MI: Upjohn Institute.

Imai, K., Keele, L., Tingley, D., & Yamamoto, T. (2011). Unpacking the Black Box of Causality: Learning about Causal Mechanisms from Experimental and Observational Studies. *American Political Science Review*, *105(4)*, 765–789.

Imbens, G. W. (2004). Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review. *Review of Economics and Statistics*, *86(1)*, 4–29.

Jacobson, L. S., & LaLonde, R. J. (2013). *Using Data to Improve the Performance of Workforce Training*. Results for America and the Brookings Institution.

Jenkins, D., & Harmon, T. (2010). *Using State Data to Promote Continuous Improvement of Workforce Programs: Guidance for States Preparing Applications to the US DOL Workforce Data Quality Initiative*. Chicago, IL: Joyce Foundation.

Johnson, H., Majia, M. C., Ezekiel, D., & Zeiger, B. (2013). *Student Debt and the Value of a College Degree*. San Francisco: CA: Public Policy Institute of California.

Long, B. T. (2010). *Grading Higher Education: Giving Consumers the Information They Need*. Center for American Progress and the Hamilton Project.

Markowitz, H. (1952). Portfolio Selection. *Journal of Finance*, *7(1)*, 77–91.

Moore, R., Chapman, K., Huber, B., & Shors, M. (2013). *Yes, But Can They Earn a Living? Methods for Creating an Effective System of Measuring Labor Market Outcomes in Higher Education* (No. CSHE.5.13). Berkeley, CA: University of California, Berkeley.

Morgan, S. L., Leenman, T. S., Todd, J. J., & Weeden, K. A. (2013). Occupational Plans, Beliefs about Educational Requirements, and Patterns of College Entry. *Sociology of Education*, *86*(3), 197–217.

Mullin, C., & Lebesch, A. (2010). *Moving Success from the Shadows: Data Systems that Link Education and Workforce Outcomes*. Washington D.C.: American Association of Community Colleges.

Mullin, C. M. (2013). *Education Workforce Outcomes Measures: Issues Facing Policymakers, Analysts, and Researchers*. American Association of Community Colleges, Washington D.C.

Mutz, D. C. (2011). *Population-Based Survey Experiments*. Princeton: Princeton University Press.

National College Access Network. (2013). *Sooner, Simpler, Smarter: Policy Change for Better College Choice*. Washington D.C.: National College Access Network. Retrieved from http://www.collegeaccess.org/collegechoice

Nielsen, H., & Vissing-Jorgensen, A. (2006). The Impact of Labor Income Risk on Educational Choices: Estimates and Implied Risk Aversion. *Unpublished Manuscript*.

Obama Administration. (2014). The College Scorecard. Retrieved from http://www.whitehouse.gov/issues/education/higher-education/college-score-card

Oreopoulos, P., & Petronijevic, U. (2013). Making College Worth it: A review of Research on the Return to Higher Education. *The Future of Children, Postsecondary Education*, *23(1), Eds., Cecilia Rouse, Lisa Barrow, and Thomas Brock.*

Owen, S., & Sawhill, I. (2013). *Should Everyone Go To College?* Washington D.C.: The Brookings Institution. Retrieved from http://www.brookings.edu/research/papers/2013/05/08-should-everyone-go-to-college-owen-sawhill

Rouse, C. E. (2004). Low-Income Students and College Attendance: An Exploration of Income Expectations. *Social Science Quarterly*, *85(5)*, 1299–1317.

Saks, R. E., & Shore, S. H. (2005). Risk and Career Choice. *The B.E. Journal of Economic Analysis & Policy*, *5*(1), 1–43.

Samii, C., & Aronow, P. M. (2012). On Equivalencies between Design-Based and Regression-Based Variance Estimators for Randomized Experiments. *Statistics and Probability Letters*, *82*, 365–370.

Schneider, M. (2013). *Higher Education Pays: But a Lot More for Some Graduates than for Others*. American Institutes for Research and CollegeMeasures.org.

Stone, C., Van Horn, C., & Zukin, C. (2012). *Chasing the American Dream: Recent College Graduates and the Great Recession*. New Brunswick: Heldrich Center for Workforce Development. Retrieved from http://www.heldrich.rutgers.edu/sites/default/files/products/uploads/Chasing_American_Dream_Report.pdf

Stuart, G. R., Rios-Aguilar, C., & Deil-Amen, R. (2014). "How Much Economic Value Does My Credential Have?" Reformulating Tinto's Model to Study Students' Persistence in Community Colleges. *Community College Review*, *42(4)*, 327–341.

U.S. Department of Labor. (2014). Workforce Data Quality Initiative. Retrieved from http://www.doleta.gov/performance/workforcedatagrant09.cfm

Voight, M., Long, A., Huelsman, M., & Engle, J. (2014). *Mapping the Postsecondary Data Domain: Problems and Possibilities*. Washington D.C.: Institute for Higher Education Policy. Retrieved from http://www.ihep.org/publications/publications-detail.cfm?id=169

Warrick, C. S., Daniels, B., & Scott, C. (2010). Accounting Students' Perceptions on Employment Opportunities. *Research in Higher Education*, *7(5)*, 1–10.

Willis, R. J., & Rosen, S. (1979). Education and Self Selection. *Journal of Political Economy*, *87(5)*, S7–36.

Wiswall, M., & Zafar, B. (2013, January). *Determinants of College Major Choice: Identification using and Information Experiment*. Federal Reserve Bank of New York Staff Reports. No. 500. Revised January 2013.

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. MIT Press. Cambridge, MA.

Zocco, D. (2009). Risk Theory and Student Course Selection. *Research in Higher Education*, *3(5)*, 1–29.