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Do Students' College Major Choices Respond to Changes in Wages?

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Abstract

We evaluate whether there is a causal connection between changes in wages by occupation and subsequent changes in the number of college majors completed in associated fields. Using aggregate national data and individual-level data from Washington State, we find statistically significant, although modest, relationships between wages and majors. College majors are most strongly related to wages observed three years earlier, when students were college freshmen. Majors with a tight connection to particular occupations show a stronger response to wages. The overall modest relationship suggests that policies which inform students about labor market outcomes are unlikely to greatly change student behavior.

"Mr. McGuire: I just want to say one word to you. Just one word.
Benjamin: Yes, sir.
Mr. McGuire: Are you listening?
Benjamin: Yes, I am.
Mr. McGuire: Plastics.
Benjamin: Exactly how do you mean?
Mr. McGuire: There is a great future in plastics. Think about it. Will you think about it?"

The Graduate (1967)

"Today's best advice, then, is that high school students who can go on to college should do so— with one caveat. They should do their homework before picking a major because, when it comes to employment prospects and compensation, not all college degrees are created equal."

Carnevale, Cheah, and Strohl (2012, p. 6)

1. Introduction and Theoretical Framework

The enormous effect of the Great Recession on the labor market and college budgets has heightened long-standing debates about which fields of study college students should major in. One view holds that students often do not sufficiently consider the economic consequences of their major choice and should be encouraged to pursue majors in high demand in the labor market (e.g., Singletary, 2012; Olson, 2012). An insufficient student response to labor market cues may affect not only their own economic well-being but also the quality of jobs available to workers in the U.S. (Holzer, 2012).[1]

There are several potential policy responses that to address the potential shortsightedness of students when choosing a course of study in college. One might, for instance, make the economic consequences of college major choice more explicit to students (Carnevale et al., 2012; Carnevale, Strohl, and Melton, 2011), or encourage students to pursue the 'right' majors by changing the relative

[1] Note that this argument implicitly assumes some degree of either myopia on the part of college students in terms of the general equilibrium effects of their college major decisions (Manski, 1993) or externalities associated with choice of college major.

price of different majors through differential tuition policies, targeted loans, or loan forgiveness.[2] Yet, as we discuss more extensively in the next section, there is only limited evidence on how these factors influence students' decisions about college major. In particular, there is very little evidence on the extent to which college students adjust their college majors in response to the information they receive about occupational earnings and fluctuations in those earnings. This is an important gap in knowledge given that arguments for guiding college students' choices of major rest on the notion that they are not as responsive as they should be to their future prospects in the labor market forshadowed by current labor market signals.[3]

In this paper we use a combination of aggregate national data and individual-level data from the State of Washington to explore the extent to which students' major choices respond to changes in the labor market at the local and national levels. Specifically, at the national level, we map college majors into different occupations and use this mapping to assess how wages for different majors changed over time. Then, we examine completed majors of students in one year and how they respond to changes in the labor market earnings in prior years. In the case of Washington State students, we examine whether changes in earnings appear to influence both one's first declared major and completed college majors.

[2] One argument is that majors viewed to be in high demand in the labor market ought to be subsidized. For instance, such a policy has been suggested by a blue ribbon task force on higher education reform in Florida, and pushed by Florida Governor Rick Scott (http://www.fgcu.edu/FacultySenate/files/2-22-2013_Resolution_Supplement_3.pdf). There is also an argument that differential pricing ought to work in the other direction. Recently, a number of higher education institutions have increased tuition in majors such as engineering and the physical sciences so as to better align tuition with the cost of instruction, and because students graduating in a high-demand major can afford higher tuition rates with their higher future salaries (Ehrenberg, 2012).

[3] Having said this, it is not entirely clear that students *ought* to be influenced by current labor market outcomes. Temporary shifts in labor market outcomes for particular occupations may have only small effects on lifetime income. Students should respond to temporary changes if they are likely to be indicative of long-term trends, or if there are strong persistent wage penalties to entering an occupation while wages are temporarily low. Some research has found that recessions and economic fluctuations can have significant and persistent effects on new college graduates that depends, in part, on the major with which they enter the labor market (Oreopoulos, von Wachter, and Heisz, 2012; Liu, Salvanes, and Sorensen, 2012).

Our theory is that students should increase their likelihood of majoring in discipline *d* if the labor market outcomes for students who majored in discipline *d* have recently improved relative to other disciplines.[4]

We find statistically significant, although modest, relationships between wages and majors at both the national and state level. Bachelor's degrees produced in year *t* are most strongly associated with wages in year *t-3*, which suggests that students' college major choice decisions respond most to wages when students are (roughly) college freshmen.[5] We also find that student response is stronger for those majors that have a tight connection to relatively few occupational choices, such as nursing. Likewise, we find that students in Washington's public universities are more responsive to wages earned by graduates from their own institution than for graduates from other state institutions or to bachelor's degree holders in the state or nationwide.

2. Background on Choice of College Major

There exists wide variation in salaries across different occupations, so one's choice of occupation has the potential to have a tremendous effect on lifetime earnings. It is no great surprise that empirical evidence generally suggests that earnings potential affects individuals' choice of occupation (e.g. Berger, 1988; Boskin, 1974; Siow, 1984; Willis and Rosen, 1979; Zarkin, 1985). In theory, forward-looking students should anticipate wage variation across occupations and accordingly choose majors that are likely to lead to preferable occupations. However, there is less definitive evidence on the extent to which lifetime earnings considerations factor into college major choices, though it is clear that there are significant differences in earnings according to one's major (Carnevale et al., 2012).

[4] While we focus on the short run connection between wage changes and academic major, wages are not the only labor market outcome that students may care about. For instance, students might also respond to the relationship between college major and unemployment or to the stability of wages over a career (Carnevale et al., 2012). Students may also respond to the variance of current wages associated with a particular major. As we discuss below, some of the measures we use do not consider the fact that students may choose a major with the intention of going on to graduate school. About half of all college graduates attend graduate school (NCES 2013) but only about one in eight college graduates matriculate immediately after graduation (NCES 2007). We expect that the students who wait after graduation to continue to graduate school are less likely to have been planning for graduate school when choosing a major.

[5] The median time to degree for 2008 bachelor's degree recipients was 4.33 years (Cataldi et al., 2011).

A theoretical basis for thinking about college major choice incorporates not only the response to earnings but also student attitudes and abilities. Different college majors require different skills. A student with very little mathematical skill will have little opportunity to successfully respond to an increase in wages for physics majors. Different college majors also offer different student experiences, and students vary in their preferences for their consumption of different learning experiences. A student who enjoys classroom discussions and writing papers may prefer the experience offered by an English major, and a student with a deep personal curiosity about power and society may prefer the experience offered by a sociology major. A student decision that places weight on consumption value or is restricted by the student's ability will display a weaker response to changes in wages.

Empirical evidence suggests that anticipated future earnings affect choice of major, but research also suggests that the influence of future earnings on college major decisions may be quite small, with the choice of major more driven by the consumption value of different fields (Arcidiacono, 2004; Beffy, Fougère, and Maurel, 2012; Wiswall and Zafar, 2013), individual aptitudes (Arcidiacono, Hotz, and Kang, 2012; Stinebrickner and Stinebrickner, 2013), or the pricing of particular majors (Stange, 2012). The primacy of consumption value appears to hold even in situations where particular majors are known to be strongly linked to certain occupations (Alstadsaeter, 2011). In particular, Berger (1988) estimates the relationship between a college students predicted future earnings and choice of major, for five broad fields of study. In models that attempt to correct for self-selection bias, assuming individual abilty and cohort affects earnings but not college major, he finds evidence suggesting that students are likely to choose majors that offer greater lifetime earnings streams (as opposed to responding primarily to initial earnings). Like Berger, Beffy et al. (2012) estimate the relationship between expected earnings and college major across broad fields of study, and they attempt to account for self-selection by exploiting variations in the relative earnings returns induced by the business cycle. They find heterogeneous responses to changes in anticipated earnings and conclude that the elasticities of major choices are modest and likely driven by non-pecuniary factors.

The research in this paper is closest in spirit to Boudarbat and Montmarquette (2007) who also estimate choice of major according to broad fields of study, and, as we do, assume that college students from a particular cohort base their decisons on what they learn about earnings by major from prior cohorts. They find that the estimated effects of initial earnings, and the rate of growth of earnings, varies by both gender and the education level of a students' parents, but generally suggests that students do respond to earnings information.

Our study contributes to the above literature in several ways. First, unlike Berger and Beffy et al., our analysis does not rely on strong rational expectations assumptions about the returns to different majors. Second, unlike prior studies, we estimate the relationship between college major and labor market earnings using very detailed information about college majors and occupational earnings, rather than a small number of aggregated categories. This allows us to assess whether the relationship between the two varies according to the tightness of the mapping between major and occupation. Third, we utilize a relatively long longitudinal panel of wage and major choice information so that we estimate the degree to what types of labor market information college students appear to respond to, e.g. the gap between occupational fluctuations in wages and college choices, and the wages of individuals of different ages. Finally, we compare findings from national samples to those at the state level, which permits an assessment of whether individuals respond to more localized (state or college specific) information about prospective wages.

3. Methods

Our methods are designed to assess the extent to which majors in discipline *d* in year *t* are influenced by the relative wages of persons who majored in discipline *d* in prior years, *t-y*. Before we discuss these methods, it is useful to consider the assumptions that are driving this analysis. The basic theory of action undergirding our model is as follows. Students get information on occupational wage changes, and form opinions about what this might mean about their future lifetime wage prospects given their college major. Based on this, they adjust their majors such that more students major in subject areas that are anticipated to lead to higher levels of compensation in the future. The connection between the information they receive about occupational wages and their college course-taking and major choices is likely to be dependent on several mediating factors. For instance, the information on salaries might be derived from local sources (e.g. recent graduates from the same college or state), or be based on national trends or news reports; it could be informed by trends in the labor market as a whole or by individuals seen by students as being a more relevant comparison (e.g. those closer in age); and students may take one or more periods (years) of information into account. Students also have to assess how occupational wages are related to the majors they receive. As we show below, while some majors are tightly linked to particular occupations, others are not. Finally, students have to make assumptions about what salaries are likely to be in the future for different occupations.

We are assuming that students perceive that a relative wage change in a given year will persist, at least to some degree, into the future. For example, students may believe that major-specific wage trajectories behave like a random walk so that shocks observed in the recent past will persist into the future. Of course, if students are responding to wage changes by changing majors and occupations, then the change to returns for majoring in discipline *d* will be moderated by the increased labor supply in discipline *d*. Thus, we are either assuming that students are partially myopic, do not understand this general equilibrium effect, or do not believe that this supply increase will completely return wages to the prior levels. Given this theory of action, changes in wages in years *t-y* should change the choice of major and ultimately lead to changes in completed majors observed in year *t*.

3.1. National Analysis

In our first analysis we calculate the correlation of the share of all degrees completed in discipline *d* in year *t* with the relative wages of persons who major in discipline *d* in years *t-y*. Figure 1 illustrates this computation for nursing. As shown below, across a 30 year span students who earned bachelor's degrees in nursing had wages that were, in an average year, 39 percent greater than persons who earned degrees in other disciplines. However, the relative wages of nurses varied quite a bit, rising steadily in the late 1980s, peaking in 1992, and falling through 2000 before rising again. The time path for the share of students earning bachelor's degrees in nursing had a similar, albeit delayed time path, rising in the mid-1990s, falling in the late 1990s, and rising again after 2002 to over 4% of all majors in 2011. We measure the correlation between the two time series; for majors measured in year *t* and associated wages measured in *t-6*, *t-5*, …, *t-1*, *t*, *t+1*, and *t+2*. As shown in the note at the bottom of Figure 1, the correlation between nursing's share of all majors in year *t* and the wages of those who major in nursing in year *t-4* is 0.387.

[Insert Figure 1 here]

We conduct this same correlation computation for each of over 1,000 different majors. We then compute the weighted average of these major-specific correlations using discipline *d*'s average share of majors across all years as its weight (e.g., nursing would get a weight of about 0.032 as this is its average share of majors). To compute the standard error of the weighted average correlation, we randomly shuffle wages across majors preserving the 1983-2012 wages of a major intact (e.g., the wage history of nursing may be randomly allocated to psychology), compute the weighted average correlation of wages and major share that emerges from this random shuffle, repeat this process 100 times, and compute the standard deviation of the weighted average correlation produced in these 100 iterations.[6] To further

[6] This method is used to address the serial correlation in wages and major shares present in the data. For a broader discussion of the use of bootstrap methods involving clusters of data, see Cameron, Gelbach, and Miller (2008).

show the strength of these relations, we run the following regression for each discipline, with wages measured with various lags, and compute the weighted average value of β_d: $M_{dt} = \alpha + \beta_d W_{dt-y} + \varepsilon_{dt}$.

To do the analyses described above, we first need to compute wages in year t for each discipline d. Doing so is a challenge as until recently there were no national datasets that contained annual information on individuals' wages and college majors (the U.S. Census Bureau has recently added college major to its American Community Survey (ACS)). Thus, to construct the time series of discipline d's wages, we first map majors to related occupations, and then compute a weighted average of wages earned in related occupations.

To construct these weights, we use two approaches. The first approach, which we label the "actual occupation approach", uses the actual pattern of occupational employment by major as found for ACS survey respondents in the years 2009 to 2011. Using these data, we find the share of major d individuals who work in occupation o and set this share as the weight when computing the weighted average wages for major d in year t.[7]

The second approach, which we call the "anticipated occupation approach", uses the major to related occupation crosswalk developed collaboratively by the National Center for Education Statistics and the Bureau of Labor Statistics (NCES/BLS, 2011). This crosswalk identifies occupations for which the major directly prepares students. The major must provide:

> "… preparation directly for entry into and performance in jobs in the SOC category. The programs satisfy requirements for entry and/or prepare individuals to meet licensure or certification requirements to work in the occupation" (p. 3).

[7] Note that the "actual occupation approach" takes into account the pathways from particular majors to graduate school and then into the labor market. So, for example, if a decent share of philosophy majors go onto law school, this approach will capture the extent to which philosophy majors should be looking at the wages of lawyers. In contrast, the "anticipated occupation approach" only captures the wages of occupations for which the major directly prepares the student, and thus may miss such graduate school pathways.

Using this crosswalk, we construct a matrix of major by occupation weights that (a) are positive if the major directly prepares the student for that occupation and zero otherwise, (b) that preserves discipline *d*'s share of all majors (averaged across years) when summed across occupations, and (c) that preserves occupation *o*'s share of all occupations (averaged across years) when summed across majors. To construct this matrix of weights, we begin with 100,000 hypothetical persons. We randomly select a major and an occupation for a person. We place this person in this major/occupation cell if (a) that major/occupation cell is "allowed" according to the NCES/BLS mapping, (b) we have not already exceeded that major's share of all majors, and (c) we have not already exceeded that occupation's share of all occupations. Ideally, we would repeat this process until all 100,000 persons had been placed. However, in practice, this process reaches a point after 45,500 persons are placed where there are no remaining cells that meet conditions (a)-(c). This result suggests that it is not possible for all persons to get jobs in occupations that match their major training if the job hiring process is not centrally planned. Since random allocation is used to generate this weighting matrix, we repeat the process described above ten times and take the average of the cell weights across these ten simulations.

After conducting the correlational analysis described above, we next test whether wages "Granger-cause" majors (Granger, 1969). That is, we test whether wages in recent years (in years *t-1* to *t-6*) in discipline *d* significantly predict the share of majors in discipline *d* in year *t* when controlling for the share of majors in discipline *d* in years *t-1* to *t-6*. For each major, we conduct the following vector autoregression:

$$M_{dt} = \alpha + \beta_{1d}M_{dt-1} + \beta_{2d}M_{dt-2} \ldots + \beta_{6d}M_{dt-6} + \gamma_{1d}W_{dt-1} + \gamma_{2d}W_{dt-2} \ldots + \gamma_{6d}W_{dt-6} + \varepsilon_{dt} \quad (1)$$

A Wald test is conducted to assess the hypothesis that the gamma coefficients are jointly zero. We report the weighted average p-value from these Wald tests, weighted by the discipline's average share of all majors. We also report the frequency by which we reject the null hypothesis across the majors we study.

3.2. Washington State Analysis

Our second analysis is designed to assess the degree to which more nuanced and localized local labor market information might influence college students' choice of major. In particular, we analyze the first declaration of major and the completion of a degree in a given major in Washington State using administrative data on undergraduates. We answer the following question: Do students shift towards more lucrative majors as measured by (a) the wages earned by recent graduates of their university, (b) recent graduates of public state universities in Washington, (c) all bachelor's degree holders in Washington, and/or (d) all bachelor's degree holders in the nation?

To examine how students change their major in 28 disciplines in response to changes in discipline-specific wages, we use the following alternative-specific conditional logit:

$$(2) \qquad p_{diut} = \frac{\exp(\alpha_d + \beta W_{dut-y} + \gamma_d X_i + \theta_d U_u)}{\sum_{d=1}^{28} \exp(\alpha_d + \beta W_{dut-y} + \gamma_d X_i + \theta_d U_u)}, \qquad d = 1, \ldots, 28,$$

p_{diut} is the likelihood of student *i* in university *u* completing (or first declaring) a degree in discipline *d* in academic year *t* (i.e., September-August). W_{dut-y} is our measure of whether wages in discipline *d* at university *u* in academic year *t-y* (where *y* is the number of years by which the wage is lagged) are unusually high for that discipline in that year. We define W_{dut-y} as follows:

$$(3) \qquad W_{dut-y} = \frac{\left[\frac{(\text{wages for discipline } d \text{ at university } u \text{ in year } t-y)}{(\text{wages for discipline } d \text{ at university } u \text{ averaged across all years})}\right]}{\left[\frac{(\text{wages for other disciplines at university } u \text{ in year } t-y)}{(\text{wages for other disciplines at university } u \text{ averaged across all years})}\right]}.$$

As an example, suppose that wages for Engineering majors in year *t-y* are 10% higher than wages for Engineering majors in a typical year, while due to a robust macroeconomy, wages for other fields are 5% higher than in a typical year. The relative wage measure in (3) would then be 1.10/1.05 = 1.048. That is, wages for Engineering majors are 4.8% higher than one would expect in year *t-y*, and thus we would expect a corresponding shift towards majoring in Engineering.[8]

Returning attention to Equation 2, X_i is a vector of demographic variables including gender, race, ethnicity, age, and age squared. In the analysis of first declared major, X_i also includes class standing (freshman/sophomore/etc.) at the time of declaration. U_u is a vector of university dummies to capture variation in the popularity of disciplines across universities. The parameter of interest in Equation 2 is β, which represents the response of major to changing relative wages. Our hypothesis is that β should be positive (when wages are contemporaneous or lagged, $y \geq 0$) – students should be more likely to choose discipline *d* if that discipline has become relatively more lucrative. We measure wages in three additional ways to get a sense of whether wage information at a less local level is more salient for students' major choices. In alternate specifications, W_{dut-y} is replaced with W_{dt-y} (i.e., dropping the *u* subscript) and wages are computed at the state level (using either recent graduates of state universities or all Washington bachelor's degree holders) or national level (using all U.S. bachelor's degree holders).

We run this specification using various lags ranging from *t-3* to *t+1* for the completed major analysis, and from *t-1* to *t+1* for the first declared major analysis.

3.3. National Analysis: Response of Majors to Popular Media Publicity

Our final analysis examines whether the production of majors nationally responds to publicity in the popular media regarding "hot" occupations. Until recently, there has been little publically provided information that would allow a student to know the level or changes in wages associated with a college major (as opposed to wages by occupation, where data from the BLS has been available for decades).[9]

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[8] We tested an analogous wage measure which computed the raw dollar difference (rather than ratios) in wages discipline *d* at university *u* in year *t-y* relative to the changes in raw dollar wages in other disciplines and the results are robust to this alternate measurement.

[9] Data that are now becoming available due to the ACS and other private sources of information (such as data from Payscale, Inc.) are making it easier for students to get a handle on wages by major. To see examples of how the popular media is conveying this information, see Goodreau (2012), Izzo (2012), Payscale, Inc. (2013), Singletary (2012), Wall Street Journal (2013), National Public Radio (2013), and Stewart (2013).

Their information about wages is likely to be informed by anecdotes and the highlighting of particular majors/occupations in the popular media. To assess the effect of the popular media, we compute the change between year *t* and year *t+y* in the share of bachelor's degrees in majors that are associated with occupations highlighted by the popular media in year *t*. We define a major *d* as associated with occupation *o* if that major prepares students to work in that occupation according to the crosswalk provided in NCES/BLS (2011).

4. Data and Empirical Counterparts

4.1. National Data on Majors

The data on completed degrees by major for the years 1987 to 2011 are taken from the Integrated Postsecondary Education Data System (IPEDS), which was collected by the U.S. Department of Education. We define majors using 6-digit Classification of Instructional Programs (CIP) codes. These CIP codes have changed periodically over time, thus we crosswalk all codes to their 2000 values using the crosswalks supplied by NCES (2013).[10] The IPEDS data is then collapsed by year to compute the total number of majors that went to each 6-digit CIP, and these totals are then converted into shares for year *t*.

4.2 National Data on Wages

The data on wages by occupation for the years 1983 to 2012 are taken from the Current Population Survey's Merged Outgoing Rotation Groups using the extracts provided by the National Bureau of Economic Research (2013). We define occupations using 3-digit Standard Occupational Classification (SOC) codes. These SOC codes have changed periodically over time, thus we use the

[10] For the years 1987-94, we first crosswalk CIP1985 to CIP1990, then again from CIP1990 to CIP2000. For the years 1995-2002, we crosswalk CIP1990 to CIP2000. For the years 2008-11, we crosswalk CIP2010 to CIP2000.

"proposed standard code" in Appendix A of Meyer and Osborne (2005) to crosswalk these codes.[11] For each of these occupations, we compute the average of weekly earnings, weighted by the individual's "earnings weight". To compute the occupation's relative wages, we then divide this figure by the weighted average of weekly earnings for all occupations in year *t*.

4.3 Washington State Data on Major and Wages

The data comes from the Education Research & Data Center (ERDC), and includes students who attended one of eight large public universities in Washington between fall 2007 and spring 2012.[12] Students' administrative records and demographic characteristics are matched to Unemployment Insurance (UI) data which records student wages after graduation. Students are linked to UI wage data using the Social Security Number provided in their baccalaureate records. 128,784 students declared a major during the sample period, and 58,511 students graduated with a bachelor's degree. When wages from the ERDC sample are used (i.e., when wages do not come from CPS data), longer lags require that students in the earlier part of the sample, for whom the lagged wage data they observe is not available to us, are dropped. For analyses that use wages from students in the ERDC sample, the sample size used in an analysis with a wage lagged by *y* is about (100-20(*Abs*(*y*))% of the full sample. Analyses using wages from the CPS sample are able to use the full sample for all lags.

For this analysis, we divide disciplines into 28 distinct fields, using the two-digit CIP classification.[13]

The earned wages associated with a particular discipline d in time *t* at university *u* is the median first-year total wages of all students who graduated with a bachelor's degree in d from university *u* in

[11] Prior to doing this crosswalk, for the years 2011-12, we first crosswalk 4-digit SOC2010 to 4-digit SOC2002 using the crosswalk supplied by U.S. Census Bureau (2013) and then collapse to 3-digit codes.

[12] These are: University of Washington campuses at Seattle, Tacoma, and Bothell; Washington State University campuses at Pullman, Spokane, Vancouver, and Tri-Cities; and Eastern Washington University.

[13] Several additional two-digit CIP codes are not used because no college in the sample offers a bachelor's degree in that discipline.

academic year t. For our alternate wage measures, we instead use median first-year total wages of all students who graduated with a bachelor's degree in d from any of our eight public Washington universities in academic year t using UI records; CPS estimate of average weekly earnings of Washington workers with bachelor's degrees working in occupations associated with discipline d; or CPS estimate of average weekly earnings of U.S. workers with bachelor's degrees working in occupations associated with discipline d. We use the "actual occupation approach" based on ACS data to map occupations to our 28 disciplines.

Annual earned wages based on the first of these wage definitions vary distinctly over time, across discipline, and across different universities. Variation in wages across disciplines explains 12% of all variation in wages across graduates, with campus attended and year respectively explaining 1% and 2% of wage variation, and 86% of wage variation remaining unexplained by discipline, campus, or time. This wage variation is uncorrelated with variation over the same period in less localized state and national data from the CPS.

When the median wage is computed for all students in the sample without differentiating by college using the second wage definition, it becomes easy to see the stark differences between annual earned wages paid to graduates from different disciplines. Figure 2 illustrates full-sample median wages for ten disciplines over the sample period. Field of study has a large effect on earned wages. In a given year, the standard deviation in wages between the disciplines each year is about $9,000. Those with computing and information services degrees and health-related degrees earn the most, with first-year wages of about $50,000 per year. Most disciplines receive wages below $30,000 per year, and the least lucrative degrees, history and foreign language, offer first-year earned wages of $17,000-$19,000 per year.

[Insert Figure 2 here]

4.4. *Occupations Receiving Popular Media Publicity*

Finally, we collected data from popular media outlets that highlighted "top occupations for the future". We focused on three media outlets: CNN, U.S. News and World Report, and the Wall Street Journal. We chose these three because they are widely read, used different methodologies to determine which occupations to highlight,[14] and the data was longitudinal. Data were obtained from CNN for the years 2003-2010, The Wall Street Journal (WSJ) for the years 2008-10, and U.S. News and World Report (USNWR) for 2009 and 2010. Most of these sources provided a list of the "Top-10" occupations ranked from 1 to 10.[15] Where possible, we mapped these occupations to associated majors using the NCES/BLS (2011) crosswalk.[16] In some cases, this mapping was not possible if the listed occupation was too specific (or vague) and did not clearly correspond to a 3-digit SOC occupation or a 6-digit CIP major (including Corporate Librarian, Environmental Specialist, Fundraiser, Intelligence Analyst, Mediator, Pharmaceutical Sales Representative, and Usability/User Experience Specialist). We also dropped "College Professor / Postsecondary Teachers" as 584 different 6-digit CIP majors are associated with "Postsecondary Teacher", so it is not clear what training students should pursue to attain this occupation.

Some of the occupations were specific enough that they mapped to only one major (including Actuary, Biomedical Engineer, Biomedical Equipment Technician, Dental Hygienist, Genetic Counselor, Hydrologist, Landscape Architect, Meeting Planner, Network Security Consultant, Nurse Practitioner, Occupational Therapist, Optometrist, Paralegal Assistant, Physician Assistant, Real Estate Appraiser,

[14] There are other sources such as MSNBC, The Washington Post, ABC News, etc. that based their information on the same underlying data as one of the three sources noted above, and thus produced occupational rankings that differ very little from those reported in the three media outlets upon which we rely.

[15] There are three exceptions. CNN provided an unranked list of the Top-10 occupations in 2003 and U.S. News and World Report provided an unranked list of the Top-30 occupations in 2009. Additionally, in 2004, CNN reported "Top 10 degrees in demand" rather than occupations.

[16] Before doing this step, since some media sources did not use 3-digit SOC titles to label occupations, we collapsed some listed occupations into single categories, including (1) Accountant / Certified Public Accountant / CPA / Accountants and Auditors; (2) Computer IT analyst / Computer Systems Analyst(s); (3) Financial Adviser / Financial Planner; (4) College Professor / Postsecondary Teachers; and (5) Software Architect / Software Engineer / Software Program Manager.

School Psychologist, Systems Engineer, and Urban Planner), while others mapped to many majors, such as Engineer (92 majors), IT Consultant (46), Maintenance and Repair Work (49), Management Consultant (64), Medical Assistants (64), and Teacher (60). There is a fair amount of subjectivity in how we chose to map the listed occupation to majors. For example, we assumed "Teacher" included pre-kindergarten to high school teacher (or teacher assistant), but not postsecondary teacher. There are no 3-digit SOC occupations with the word "Consultant" and only one 6-digit CIP major ("Fashion and Fabric Consultant"). As a result, for "IT Consultant" and "Management Consultant", we assumed that students would, respectively, seek training in information technology (and related fields) or management, which thus leads to a large number of possible majors leading to these occupations. Our challenge in mapping these listed occupations to majors would be faced by students in making sense of these Top-10 lists; in many cases, there simply is not a clearly correct way to translate these lists into actionable course-taking choices.

It is also worth noting that there was not a high degree of correspondence across the three media sources in the occupations that they highlighted in a given year. In 2008, a total of 18 distinct occupations were highlighted on CNN's and WSJ's Top-10 lists. In 2009, 47 (out of a maximum possible 50) distinct occupations were listed in CNN's and WSJ's Top-10 lists and USNWR's Top-30 list. Finally, in 2010, 28 (out of a maximum possible 30) distinct occupations were listed in the three media sources' Top-10 lists. There was also not great year-to-year stability in the highlighted occupations; across these three media sources and across these years a total of 85 distinct occupations were highlighted (out of a maximum possible 140). This variation of information across sources and across years would make it more difficult for students to know how to respond to this information.

5. Results

5.1. National Analysis

Table 1 shows our results using the "actual occupation approach". Column 1 shows the relation of wages in major *d* and the awarding of bachelor's degrees in major *d*, with no restrictions on the CPS sample of workers. In this column, we find the peak correlation is 0.140 for bachelor degree majors in year *t* with wages for all workers in year *t-3*. Squaring this correlation produces an R-squared of 0.02. That is, variation in wages for all workers in affiliated occupations in year *t-3* explains only about 2% of the variation in the production of bachelor degrees in year *t*. The weighted average effect of wages in major *d* in year *t-3* on the share of bachelor's degrees going to major *d* in year *t* is 0.014.[17] To put this figure into context, if major *d* experienced a robust 0.1 increase in relative wages, perhaps going from 1.0 (average wages) to 1.1 (10% above average wages), then that major's share would be expected to rise by 0.0014 (0.14 percentage points). Note that the weighted average major has a share of all bachelor's degrees of 0.0207 (or 2.07%). Thus, a 0.1 increase in relative wages would increase this average major's share from 2.07% to 2.21%, for an elasticity of about 0.7. Whether this response is large or small is in the eye of the beholder, but we view this change as modest. Interestingly, these results are close to, but somewhat smaller than, those in Beffy et al. (2012). They simulate that a 10% increase in wages would, respectively, lead to a 0.25, 0.53, and 0.40 percentage point increase in the share of students majoring in sciences; humanities and social sciences; and law, economics, and management. They characterize their results as "quantitatively small even though they are statistically significant" (p. 342), and we share this conclusion.

In columns 2-4, we restrict the CPS sample to individuals with a bachelor's degree, to those aged 30 and under, or to those aged 30 and under with a bachelor's degree. Our theory is that 4-year college students may be more responsive to the wages earned by individuals with a bachelor's degree and/or to

[17] These regression results are not shown, but are available from the authors.

those aged 30 and under as the wages of these persons may be a better signal of the college student's future labor market prospects. We, however, find little support for this theory. The correlations are *not* stronger when we restrict the CPS wage data in these ways. The last two columns of Table 1 show the results using majors for any "degree" (including bachelor's and associate's degrees, certificates, etc.). The results are similar, although the peak correlations are at shorter lags (e.g., *t-2* and *t-0* in columns 5 and 6), which makes sense as the added degrees take less time to complete.[18] Overall, we find that changes in the production of majors is only modestly related to changes in the labor market, and it appears that students may be drawing information from the full range of employed individuals in the labor market (rather than younger individuals with bachelor's degrees) when making their major choices.

[Insert Table 1 here]

Table 2 presents the results using the NCES-BLS recommended major-to-occupation correspondences (the "expected occupation approach"). The patterns are similar, although the correlations are smaller and less likely to be statistically significant. One possible explanation is that students' major choices are more affected by the actual labor market relationships than by the wages in occupations for which the major is supposed to train the student.[19] For the remainder of the paper, we use actual occupation approach.

[Insert Table 2 here]

[18] One might be concerned by some of the significant positive correlations between majors in year *t* and wages in year *t+1* or *t+2*. Theoretically, these correlations should be negative – the production of more supply of workers trained in discipline *d* should depress their wages on the labor market. However, looking at Figure 1 helps illustrate why we may be observing these results. For nursing, wages rise and fall in waves that last several years. It may take several large cohorts of newly trained nurses to cause wages to fall.

[19] Another possibility is that measurement error in wages by major is smaller for the actual occupation approach as it averages wages from more occupations, and thus may result in less attenuation bias than the expected occupation approach.

To help explain the relatively small correlations found in Tables 1 and 2, we explored two hypotheses. The first hypothesis is that students may be more responsive to wages in majors that have tighter connections to particular occupations; some research, for instance, suggests that a significant share of workers are employed in jobs that are not closely aligned with their educational specialization, but this is less true for some specific field programs (Boudarbat and Chernoff, 2009). Using the ACS data, we computed each major's index of qualitative variation (IQV), which ranges from 0.0 (when all persons with major *d* are employed in occupation *o*) to 1.0 (when persons with major *d* are evenly spread across all occupations).[20] We split the sample of majors by those that were above or below the median IQV. The results are shown in Table 3. We find strong evidence suggesting that students may have better information about wages for majors that feed into fewer occupations. The correlation between wages in year *t-3* and majors in year *t* is 0.305 (p≤0.01) for majors with tight connections to particular occupations and only 0.096 (p>0.10) for majors with loose connections to particular occupations.

[Insert Table 3 here]

Our second hypothesis is that students may have better information about wages for the largest, most popular majors, and thus may be more responsive to wage changes for those majors. Table 4 tests this hypothesis and finds no support for it. The first column of this table reproduces Table 1 column 1 for comparison. The subsequent columns of Table 4 successively restrict the analysis to bigger and bigger majors. For example, as shown in column 2, 90% of bachelor's degrees are earned in 165 majors. However, the correlations are modestly smaller in column 2 than in column 1, failing to support the hypothesis that students respond more heavily to wage changes in larger majors. This result is maintained with further restrictions in column 3 (where 75% of bachelor's degrees are earned in 64 majors) and column 4 (where 50% of bachelor's degrees are earned in only 17 majors).

[Insert Table 4 here]

[20] We calculate IQV using the M2 index (Gibbs and Poston, 1975): $IQV_d = \frac{K}{K-1}(1 - \sum_o^K p_{do}^2)$ where p_{do} is the share of graduates of discipline *d* who end up in occupation *o* and *K* is the total number of occupations.

Table 5 summarizes the results of our tests that prior wages in discipline *d Granger-cause* bachelor's degrees in *d* in year *t*. We have enough data to test this hypothesis for 1,062 majors. As shown in column 1, the weighted average p-value of the test of Granger-causality is 0.104 and the p-value is ≤ 0.05 for 840 majors. As we restrict the CPS sample used to identify wages to individuals with a bachelor's degree, to those aged 30 and under, or to those aged 30 and under with a bachelor's degree (columns 2-4), the weighted average p-value successively falls (and is 0.031 in column 4). However, the number of majors with significant evidence of Granger-causality is relatively unchanged with the CPS sample restrictions. Finally, in columns 5 and 6, we split the sample by the majors' IQV scores (as was done in Table 3). We find somewhat stronger evidence of Granger-causality for majors that feed fewer occupations than for majors with weaker connections to particular occupations.

[Insert Table 5 here]

5.2 Washington State Analysis

Table 6 displays student response to wages in the Washington State sample. Each reported coefficient and average marginal effect is from a separate analysis. In Panel A, we show the results for completed major. We find that the largest significant marginal effects are found for wages with a three-year lag based on recent graduates of public universities in the State of Washington (0.017 with respect to recent graduates of the student's own university and 0.018 with respect to recent graduates from any of the eight universities in our data). A marginal effect of 0.018 suggests that if a major saw its wages rise 10% more than one would expect in year *t-3*, then the share of students completing that major in year *t* would increase by only 0.18 percentage points. Again, we would characterize this response as modest, and it is notably similar to the magnitude we find in the national analysis.

[Insert Table 6 here]

Panel B shows the results for student's first declaration of a major. The largest significant marginal effects are found for wages with a one-year lag based on all bachelor's degree holders (0.034

with respect to bachelor's degree holders in Washington and 0.027 with respect to bachelor's degree holders nationally). As students move from the first declaration of a major to actually completing a major, it appears that they shift from being influenced by data on all adults with bachelor's degrees to more localized information on recent peers. It is unclear whether this responsiveness to local labor market conditions is a good choice for students. On the one hand, it may help them immediately get a well-paying job. On the other, if the local labor market trends are different from national trends, it could reduce the student's national labor market prospects and ultimately reduce the student's capacity for mobility. Such reduced mobility may lead to higher unemployment as it limits the ability of labor markets to adequately adjust to shifts in labor demand (Bound and Holzer, 2000; Holzer, 1991).

5.3 Analysis of Occupations Highlighted by Popular Media

Finally, we find scant evidence that students increase their likelihood of choosing to major in a field associated with an occupation highlighted by the popular media in prior years. As shown in in the Panel A of Table 7, it appears that students respond *negatively*, if at all, to such occupational highlighting. In the eight years from which we obtained data on occupational highlighting in the popular media, the share of majors that are associated with the highlighted occupations ranged from 13.0% in 2005 (when only CNN highlighted occupations) to 40.5% in 2009 (when all three media sources highlighted occupations, and when USNWR listed the Top-30 occupations). In the years following these reports, on average, the share of these majors among all degrees fell by 0.4, 0.7, 1.0, and 1.0 percentage points in years *t+1*, *t+2*, *t+3*, and *t+4*, respectively.

[Insert Table 7 here]

The results shown in Panel A of Table 7 are for all degrees. When we restrict the analysis to bachelor's degrees (results not shown), we find a similar pattern, with declines of 0.3, 0.6, 1.0, and 1.1 percentage points, respectively. Further, we hypothesized that students may respond more positively to occupations ranked at the top of these lists. When we restrict the analysis to occupations highlighted as amongst the top-3 best (results not shown), we find smaller effects, with a 0.1 decline in *t+1*, no change in *t+2*, and declines of 0.2 percentage points in years *t+3* and *t+4*.

Finally, as shown in Panel B of Table 7, we restrict the analysis to those occupations that map to only 1, 2, or 3 majors. Our theory is that highlighting of these occupations creates a more clearly "actionable" choice for students than occupations connected to more majors. In the first and third rows of this panel, which show the changes in majors related to highlighted occupations for 2003 (IT Security, Investigator, and Physical Therapist) and 2005 (Environmental Engineer, Medical Records and Health Information Technicians, and Physician Assistant), we do find evidence that the associated majors increased shares in the subsequent years. However, for highlighted occupations in 2004 and 2006-10, the changes in associated majors are smaller and inconsistently signed. Thus, overall, we conclude that there is not substantial evidence that information conveyed by the popular media is substantially affecting student major choices.

6. Implications for Policymakers and Conclusions

In this paper we find that students' choice of major responds positively to longitudinal changes in relative wages. However, we see this response as modest, with variation in wages leading to small changes in major declaration and degree production, a finding that is generally consistent with other work investigating the connection between labor market earnings and college major choices (Beffy et al., 2012).

This result is not wholly surprising. To the degree that students would like to respond to changes in the labor market, there is a severe lack of information available which would allow them to respond adequately. Information about earnings based on major choice is rarely available or accessible. Information about earnings based on occupations is more easily available, but students attempting to use this information face another stumbling block: many majors lead to a wide range of occupations, and thus it is difficult for students to make choices about field of study based on the wages of those occupations. But, we also find evidence that in situations where labor market information is likely to be more reliable or useful - in the case of majors closely associated with particular occupations, or in the case of wage data collected at the most local level – student response to wages is stronger.

Access to usable information about wages has been improving. Payscale.com was an early private provider of information about the wages associated with different college majors, and until recently has had little competition. The inclusion of a field of study variable in the ACS data beginning in 2008 allows a more rigorous public presentation of wages by major, with the report by Carnevale et al. (2012) receiving wide news coverage. These sources of data provide more usable information to students and could make it easier for them to respond to wage changes. Interestingly, and somewhat at odds with this hypothesis however, information available to college students from popular media outlets that highlight the benefits of cerain occupations did not change major choice in the predicted direction, suggesting that this information was inaccessible, untrusted, or ignored by students.

Our findings from Washington State suggest that students are more likely to respond to localized information about earnings than national information, which may well be desirable since there are good arguments for better alignment between education systems and labor demand (Holzer, 2012). But it does not necessarily follow that policymakers ought to push for the provision of more localized information about the returns to particular majors. As we have shown, the provision of this sort of information requires some guesswork about how majors map onto occupations, and, more generally, the provision of information may or may not predict the true long-run economic prospects of majoring in a particular field. Moreover, given that sectoral shifts do not always align at the local and national levels (Bound and Holzer, 2000), it is possible that a response to local labor market information could serve to limit students' national labor market mobility.

Regardless of the efficacy of trying to shape individuals' college major choices, it appears that this is the direction in which policy is heading. Some differential tuition policies aim to put more students into high-demand majors. President Obama has laid out a plan to publicly rate colleges in part based on the earnings of graduates, which ties the success of colleges to their ability to produce high earners. Inherent in these plans is a public policy goal that degree production responds more strongly to the demands of the labor market, whether this responsiveness occurs at the level of the student or in changes in college offerings.

Given our results, it seems that policies which provide information about future labor market returns are likely to have smaller effects on student choice than differential tuition interventions (Stange, 2012) or more direct career counseling. Student response to signals of labor market demand, even in a long time frame, are relatively modest.

Better quality information or additional institutional emphasis on the labor market may increase student responsiveness to labor market cues. However, we find mixed evidence on the effect of improved information, with students responding more closely to local data but not responding properly to news reports about occupations. An intervention which aims to improve student responsiveness to labor market cues with information provision alone runs into a problem in that student responsiveness to the labor market is so modest to begin with. An informational intervention alone would need to have very large effects in order to lead to a landscape in which student response to the labor market might be considered adequate by policymakers.

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Tables and Figures

Figure 1: Wages and Share of Bachelor's Degrees in Nursing

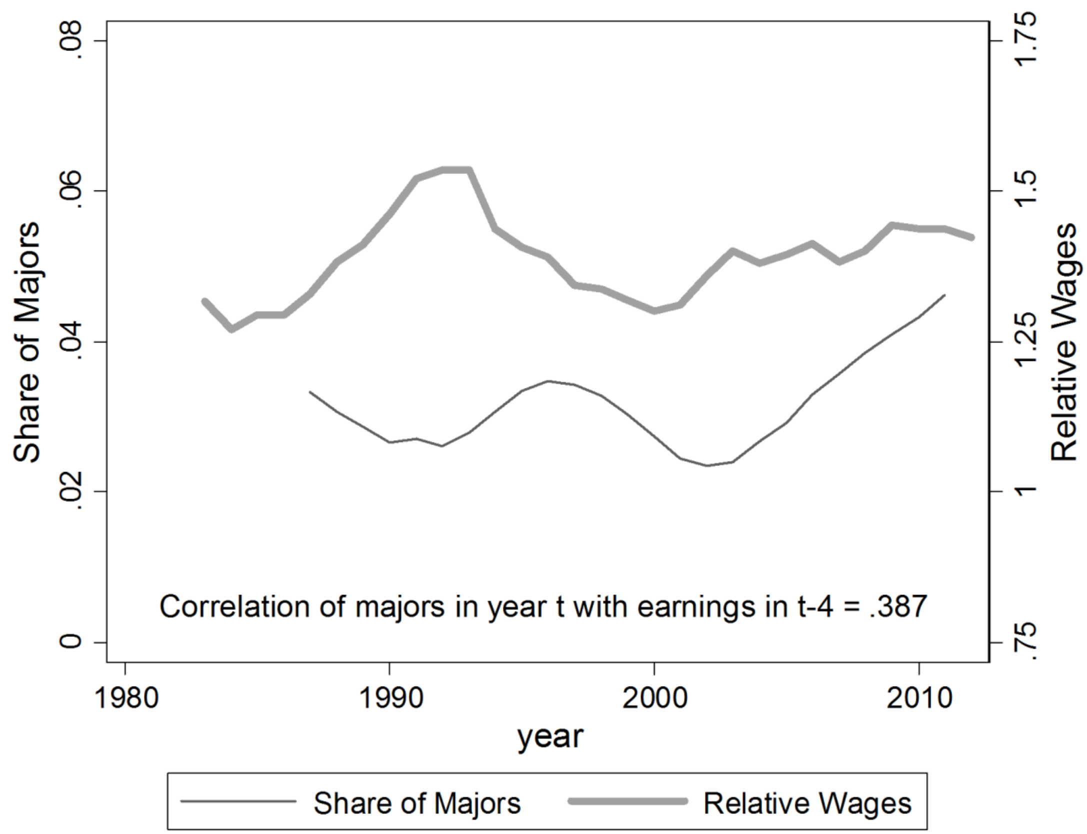

Figure 2: Median First-Year Wages in Ten Selected Disciplines over Time

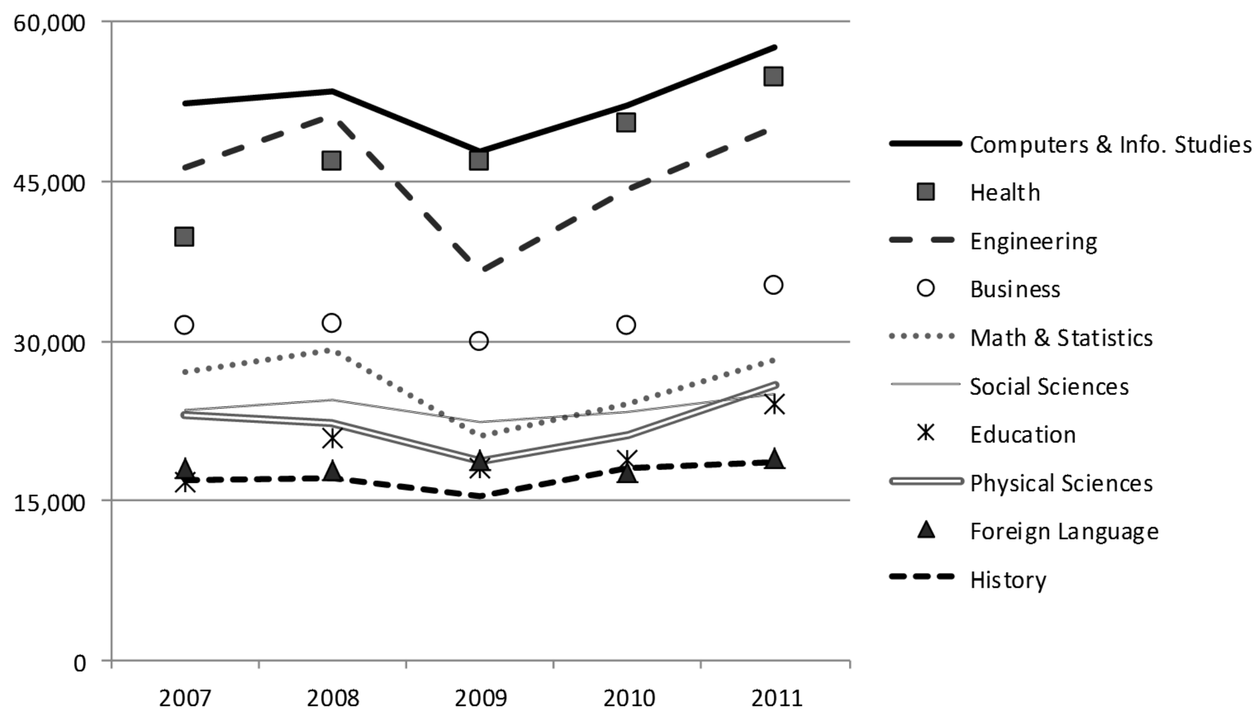

Table 1: Correlation Between Majors Produced in Year *t* and Associated Occupational Wages in Year *t-y*, with Mapping from Majors to Occupations done using Observed Pattern in American Community Survey Data.

	(1)		(2)		(3)		(4)		(5)		(6)	
IPEDS Majors Awarded for:	**Bachelors Degrees**		**Bachelors Degrees**		**Bachelors Degrees**		**Bachelors Degrees**		**All Degrees**		**All Degrees**	
CPS Wages Restricted to Bachelor's Degree Holders?	**No**		**Yes**		**No**		**Yes**		**No**		**No**	
CPS Wages Restricted to Age 30 and Under?	**No**		**No**		**Yes**		**Yes**		**No**		**Yes**	
Wages Measured in Year:	**Correlation of Share of Majors in Year *t* with Wages for that Major**											
t+2	0.008		0.066		-0.004		0.011		0.051		0.062	+
	(0.046)		(0.050)		(0.050)		(0.033)		(0.037)		(0.041)	
t+1	0.047		0.077	+	0.027		0.031		0.087	**	0.088	**
	(0.046)		(0.052)		(0.051)		(0.036)		(0.037)		(0.042)	
t	0.078	*	0.095	*	0.039		0.050		0.115	***	**0.093**	**
	(0.047)		(0.056)		(0.052)		(0.040)		(0.037)		**(0.040)**	
t-1	0.111	**	0.115	*	0.061		0.076	*	0.125	***	0.079	**
	(0.048)		(0.062)		(0.051)		(0.044)		(0.038)		(0.039)	
t-2	0.130	***	0.115	*	0.063		0.093	*	**0.130**	***	0.053	
	(0.049)		(0.065)		(0.052)		(0.048)		**(0.039)**		(0.040)	
t-3	**0.140**	***	0.123	*	**0.078**	+	**0.117**	**	0.127	***	0.049	
	(0.051)		(0.070)		**(0.051)**		**(0.053)**		(0.041)		(0.042)	
t-4	0.135	***	**0.131**	*	0.067		0.113	**	0.119	***	0.063	+
	(0.051)		**(0.070)**		(0.051)		(0.053)		(0.042)		(0.042)	
t-5	0.132	***	0.123	*	0.022		0.081	+	0.119	***	0.041	
	(0.051)		(0.070)		(0.050)		(0.054)		(0.042)		(0.044)	
t-6	0.116	**	0.099	+	-0.021		0.042		0.115	***	0.029	
	(0.050)		(0.067)		(0.049)		(0.055)		(0.041)		(0.044)	

Note: ***, **, *, and + denote two-tailed significance at the 1%, 5%, 10%, and 15% levels respectively. Bolded values reflect the peak correlation for the column.

Table 2: Correlation Between Majors Produced in Year *t* and Associated Occupational Wages in Year *t-y*, with Mapping from Majors to Occupations done using Crosswalk Developed Jointly by the National Center for Education Statistics and the Bureau of Labor Statistics.

	(1)		(2)		(3)		(4)		(5)		(6)	
IPEDS Majors Awarded for:	**Bachelors Degrees**		**Bachelors Degrees**		**Bachelors Degrees**		**Bachelors Degrees**		**All Degrees**		**All Degrees**	
CPS Wages Restricted to Bachelor's Degree Holders?	**No**		**Yes**		**No**		**Yes**		**No**		**No**	
CPS Wages Restricted to Age 30 and Under?	**No**		**No**		**Yes**		**Yes**		**No**		**Yes**	
Wages Measured in Year:	**Correlation of Share of Majors in Year *t* with Wages for that Major**											
t+2	-0.007		-0.040		-0.023		-0.037		-0.017		0.018	
	(0.055)		(0.056)		(0.053)		(0.044)		(0.048)		(0.043)	
t+1	0.009		-0.038		-0.023		-0.034		0.002		0.022	
	(0.057)		(0.059)		(0.052)		(0.041)		(0.046)		(0.043)	
t	0.039		-0.016		-0.024		-0.027		0.024		0.027	
	(0.059)		(0.064)		(0.051)		(0.042)		(0.047)		(0.044)	
t-1	0.064		0.016		-0.013		-0.002		0.039		0.049	
	(0.060)		(0.065)		(0.049)		(0.043)		(0.049)		(0.046)	
t-2	0.089	+	0.048		0.005		0.023		**0.056**		0.059	
	(0.062)		(0.067)		(0.051)		(0.043)		**(0.050)**		(0.048)	
t-3	0.119	*	0.086		0.018		0.047		0.047		0.052	
	(0.062)		(0.065)		(0.050)		(0.048)		(0.050)		(0.051)	
t-4	**0.134**	**	**0.098**	+	**0.048**		**0.069**		0.046		**0.076**	+
	(0.062)		**(0.063)**		**(0.051)**		**(0.051)**		(0.049)		**(0.048)**	
t-5	0.131	**	0.091	+	0.042		0.067		0.050		0.064	
	(0.062)		(0.061)		(0.052)		(0.051)		(0.049)		(0.049)	
t-6	0.112	*	0.077		0.025		0.048		0.033		0.047	
	(0.061)		(0.059)		(0.050)		(0.051)		(0.049)		(0.049)	

Note: ***, **, *, and + denote two-tailed significance at the 1%, 5%, 10%, and 15% levels respectively. Bolded values reflect the peak correlation for the column.

Table 3: Is the Observed Correlation between Bachelor's Degree Majors and Wages Higher for Majors with "Tighter" Connections to Particular Occupations

	(1)		(2)	
Connection of Major to Occupations	**Tight:** At or below Median Major		**Loose:** Above Median Major	
Wages Measured in Year:	**Correlation of Share of Majors in Year *t* with Wages for that Major**			
t+2	0.132	*	-0.059	
	(0.077)		(0.057)	
t+1	0.160	**	-0.022	
	(0.076)		(0.057)	
t	0.183	**	0.020	
	(0.077)		(0.055)	
t-1	0.221	***	0.064	
	(0.076)		(0.057)	
t-2	0.271	***	0.081	
	(0.077)		(0.060)	
t-3	0.305	***	**0.096**	+
	(0.080)		**(0.059)**	
t-4	**0.327**	***	0.088	+
	(0.081)		(0.058)	
t-5	0.322	***	0.089	+
	(0.084)		(0.057)	
t-6	0.293	***	0.083	+
	(0.083)		(0.052)	

Note: ***, **, *, and + denote two-tailed significance at the 1%, 5%, 10%, and 15% levels respectively. Bolded values reflect the peak correlation for the column. Mapping from majors to occupations done using observed pattern in American Community Survey data.

Table 4: Is the Observed Correlation Between Majors and Wages Higher for the Larger Majors?

	(1)		(2)		(3)		(4)	
Share of all Bachelor's Degrees	**100%**		**90%**		**75%**		**50%**	
Number of Distinct Majors Included	**1,101**		**165**		**64**		**17**	
Wages Measured in Year:	**Correlation of Share of Majors in Year *t* with Wages for that Major**							
t+2	0.008		0.000		-0.005		-0.005	
	(0.046)		(0.044)		(0.054)		(0.054)	
t+1	0.047		0.042		0.039		0.039	
	(0.046)		(0.046)		(0.057)		(0.057)	
t	0.078	*	0.072	+	0.071		0.071	
	(0.047)		(0.048)		(0.060)		(0.060)	
t-1	0.111	**	0.103	**	0.106	*	0.106	*
	(0.048)		(0.049)		(0.063)		(0.063)	
t-2	0.130	***	0.118	**	0.121	*	0.121	*
	(0.049)		(0.050)		(0.064)		(0.064)	
t-3	**0.140**	*******	**0.124**	******	**0.127**	*****	**0.127**	*****
	(0.051)		**(0.052)**		**(0.066)**		**(0.066)**	
t-4	0.135	***	0.115	**	0.116	*	0.116	*
	(0.051)		(0.051)		(0.066)		(0.066)	
t-5	0.132	***	0.108	**	0.106	*	0.106	*
	(0.051)		(0.050)		(0.064)		(0.064)	
t-6	0.116	**	0.084	*	0.079		0.079	
	(0.050)		(0.049)		(0.062)		(0.062)	

Note: ***, **, *, and + denote two-tailed significance at the 1%, 5%, 10%, and 15% levels respectively. Bolded values reflect the peak correlation for the column. Mapping from majors to occupations done using observed pattern in American Community Survey data.

Table 5: Do Wages in Years *t-1* to *t-6* Granger-Cause Bachelor Degree Majors in Year *t*?

	(1)	(2)	(3)	(4)	(5)	(6)
CPS Wages Restricted to Bachelor's Degree Holders?	**No**	**Yes**	**No**	**Yes**	**No**	**No**
CPS Wages Restricted to Age 30 and Under?	**No**	**No**	**Yes**	**Yes**	**No**	**No**
Sample Restriction	**None**	**None**	**None**	**None**	**Majors with Tighter Connections to Occupations**	**Majors with Looser Connections to Occupations**
Weighted Average P-Value	0.104 +	0.049 **	0.035 **	0.031 **	0.046 **	0.088 *
Total Majors Evaluated	1,062	1,062	1,062	1,062	522	540
Majors with P-Value <= 0.1	899 (85%)	919 (87%)	816 (77%)	829 (78%)	457 (88%)	435 (81%)
Majors with P-Value <= 0.05	840 (79%)	853 (80%)	750 (71%)	772 (73%)	427 (82%)	404 (75%)
Majors with P-Value <= 0.01	721 (68%)	715 (67%)	647 (61%)	622 (59%)	379 (73%)	338 (63%)

Note: ***, **, *, and + denote weighted average p-value at or below the 1%, 5%, 10%, and 15% levels respectively. Granger test conducted using six lags of wages and six lags of majors used to predict majors in year *t*.

Table 6: Do Students' Completed and Declared Majors Respond to Local Labor Market Wages?

	(1)		(2)		(3)		(4)	
Source of Wage Data	**UI**		**UI**		**CPS**		**CPS**	
Level of Wage Data	**Recent Graduates of Own University**		**Recent Graduates of Eight Public Universities in Washington State**		**Washington State Bachelor's Degree Holders**		**National Bachelor's Degree Holders**	
Wages Measured in Year:			**Panel A: Completed Major**					
t+1	-0.020		-0.012		0.099		-0.055	
	(0.050)		(0.087)		(0.090)		(0.242)	
	[-0.001]		[0.000]		[0.003]		[-0.002]	
t	0.102	***	0.070		-0.322	***	-0.070	
	(0.034)		(0.066)		(0.085)		(0.309)	
	[0.003]		[0.002]		[-0.010]		[-0.002]	
t-1	0.044		0.057		0.240	***	-0.041	
	(0.038)		(0.072)		(0.078)		(0.344)	
	[0.001]		[0.002]		[0.008]		[-0.001]	
t-2	-0.058		-.141*		0.030		0.363	
	(0.050)		(0.082)		(0.060)		(0.305)	
	[-0.002]		[-0.005]		[0.001]		[0.012]	
t-3	0.503	***	0.553	***	0.108	**	0.115	
	(0.107)		(0.170)		(0.060)		(0.284)	
	[0.017]		[0.018]		[0.004]		[0.004]	
			Panel B: First Declared Major					
t+1	0.176	***	0.125	*	0.165	***	-0.279	
	(0.031)		(0.064)		(0.071)		(0.195)	
	[0.006]		[0.004]		[0.005]		[-0.009]	
t	0.074	***	0.072		-0.097	*	-0.265	
	(0.023)		(0.049)		(0.050)		(0.170)	
	[0.002]		[0.002]		[-0.003]		[-0.009]	
t-1	0.071	***	0.127	**	1.022	***	0.809	***
	(0.026)		(0.055)		(0.046)		(0.180)	
	[0.002]		[0.004]		[0.034]		[0.027]	

Note: ***, **, *, and + denote two-tailed significance at the 1%, 5%, 10%, and 15% levels respectively. Standard error of β is in parentheses. Average marginal effect is in brackets.

Table 7: Do Students' Majors Respond to Popular Media?

	Year When Occupations Were Highlighted by the Popular Media (*t*)	Share of Majors in Year *t* Associated with Highlighted Occupations	Change in Share of Majors Associated with Highlighted Occupations Between Year *t* and: Year *t+1*	Year *t+2*	Year *t+3*	Year *t+4*	Year *t+5*	Year *t+6*	Year *t+7*	Year *t+8*
Panel A: All Highlighted Occupations	**2003**	16.1%	-0.5%	-1.0%	-1.5%	-1.5%	-1.3%	-1.0%	-1.1%	-1.0%
	2004	19.9%	-1.0%	-1.6%	-1.8%	-1.9%	-1.7%	-2.1%	-2.4%	--
	2005	13.0%	-0.3%	-0.6%	-0.7%	-0.1%	1.1%	1.6%	--	--
	2006	20.8%	-0.3%	-0.3%	-0.3%	-0.8%	-1.3%	--	--	--
	2007	23.3%	*0.0%*	*0.0%*	-0.6%	-0.7%	--	--	--	--
	2008	18.0%	-0.3%	-0.6%	-0.9%	--	--	--	--	--
	2009	40.5%	-0.7%	-0.8%	--	--	--	--	--	--
	2010	27.3%	-0.3%	--	--	--	--	--	--	--
	Average	22.4%	-0.4%	-0.7%	-1.0%	-1.0%	-0.8%	-0.5%	-1.7%	-1.0%
Panel B: Highlighted Occupations the Map to Only 1, 2, or 3 Majors	**2003**	0.72%	0.10%	0.14%	0.17%	0.17%	0.17%	0.16%	0.17%	0.19%
	2004	0.85%	-0.03%	-0.02%	-0.02%	*-0.01%*	-0.04%	-0.03%	-0.02%	--
	2005	0.59%	*0.00%*	*0.00%*	0.03%	0.09%	0.21%	0.35%	--	--
	2006	0.28%	-0.04%	-0.05%	-0.07%	-0.07%	-0.08%	--	--	--
	2007	0.12%	*0.00%*	0.01%	*0.00%*	-0.01%	--	--	--	--
	2008	0.39%	0.02%	0.01%	0.01%	--	--	--	--	--
	2009	1.89%	*0.01%*	*-0.01%*	--	--	--	--	--	--
	2010	1.11%	*0.01%*	--	--	--	--	--	--	--
	Average	0.74%	0.01%	0.01%	0.02%	0.04%	0.06%	0.16%	0.08%	0.19%

Note: All changes are significant at the 5% level except those changes that are italicized.