



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

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Abstract: We find statistically significant relationships between changes in wages by occupation and subsequent changes in college majors completed in associated fields. College majors (defined at a detailed level) are most strongly related to wages observed three years earlier, when students were college freshmen. The responses to wages vary depending on the extent to which there is a strong mapping of majors into particular occupations. We also find that women and black students are less likely to respond to wage changes. These findings have implications for policy interventions designed to align students' major choices with labor market demand.

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“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

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 choices and should be encouraged to pursue majors in high demand in the labor market (e.g., Singletary, 2012; Olson, 2012). The presumption here is that an insufficient student response to labor market cues, due to students not having enough labor market information or to externalities associated with choice of college major, may affect not only their own economic well-being but also the quality of jobs available to workers in the U.S. (Holzer, 2012).

There are several potential policy responses to address potential market failures that lead to suboptimal student choices. One might, for instance, make the economic consequences of college major choice more explicit to students (Carnevale et al., 2011, 2012), or encourage students to pursue the ‘right’ majors by changing the relative price of different majors through differential tuition policies, targeted loans, or loan forgiveness. Some argue that majors with high labor market demand ought to be subsidized in order to encourage higher enrollment in those areas. Such a policy has been suggested by a blue ribbon task force on higher education reform in Florida, and advocated by Florida Governor Rick Scott.¹

¹ Interestingly, however, in contrast to the idea of subsidizing in-demand majors, 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).

It is reasonable to argue that whether, and how, policy interventions ought to help students align their college major choices with their financial self interests. Whether or not help may be justified, and the efficacy of different types of interventions, depends a great deal on the degree to which students themselves are sensitive to the labor market returns associated with their choices. Interestingly, there is insufficient empirical evidence on this basic labor market issue. In this paper we estimate the reaction of students' college major choices to changes in associated wages. Specifically, we assess: 1) the sources of wage information to which students respond (e.g. national or local labor market); 2) the types of majors in which degree production is most responsive; and 3) whether there is heterogeneity in student responses. We rely on a combination of aggregate national data and individual-level longitudinal data from the State of Washington. These data allow us, at the national level, to map college majors into different occupations and use this mapping to assess how wages for different majors changed over time, and then to link these changes to information about completed college majors to see how these respond to changes in the labor market earnings in prior years. In the case of Washington State students, we investigate whether local, state, or national wage information has the most impact on choices, and look for heterogeneity in responses by student characteristics.

We find statistically significant relationships between wages and majors at both the national and state level and with majors defined at both detailed and aggregated levels. Bachelor's degrees produced in year t in detailed majors 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.²

We also find that student response is stronger for those majors that have a tight connection to relatively few occupational choices, such as nursing. Our results from Washington state confirm the national analysis, and we also find that students are more responsive to wages earned by recent graduates from public institutions in Washington than to wages earned by all bachelor's degree holders in the state or nationwide. Finally, we show that women and African-American students are less likely to respond to changes in local wages than other students: their responses are about half the size of men and white students.

These results inform how we think about the strength of student response to wages. For an average sized major, an increase in that major's wages of 10% relative to the wages of other

² The median time to degree for 2008 bachelor's degree recipients was 4.33 years (Cataldi et al., 2011).

majors would lead the share of degrees earned in that major to increase from 2.07% to 2.21%, a figure which is unlikely to lead to a world in which degree production aligns strongly with labor market demands. If policy goals entail a strong alignment, these results could act as justification for policy which guides student choice. However, we find that majors like Pharmaceuticals and Drug Design, which are tightly connected to particular occupations, experience responses that are substantially greater than those for majors that are loosely connected to occupations.

Many of the college majors which are at the center of policy interventions, in particular STEM majors, are among those with relatively stronger responses to wages already. Some policy makers may consider the response to be still too weak. However, it appears that students who consider majoring in these fields do take labor market returns into account when choosing a major. We cannot say whether the lower response rate for women and African-American students is related to the types of labor market information these groups receive or differences in preferences for major. However, our findings on heterogeneity amongst student subgroups suggest that the lower responsiveness to wage changes for these subgroups may help explain why they tend to be underrepresented in certain majors and occupations that hire those majors.

2. Theoretical Framework

The theory undergirding our analysis is simple: students should increase their likelihood of majoring in discipline d if they anticipate that there are increasing economic rewards associated with majoring in discipline d . And further, that students gauge the economic rewards associated with majoring in discipline d , at least in part, based on the labor market outcomes for students who recently received degrees in this discipline.³

We illustrate this theoretical framework in Figure 1. In this stylized example, the demand curve in this graph is a weighted average of labor demand for newly graduated employees in occupations associated with major d , with weights based on the share of students who major in d and are subsequently employed in occupation o .⁴ Likewise, the labor supply curves in this graph

³ While we focus on the short run connection between wage changes and academic major, we want to acknowledge that 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. Unfortunately, the data do not permit us to delve into these issues in any detail.

⁴ This stylized model ignores potentially important factors such as changes over time in the share of students from major d that choose to work in occupation o , which are likely to be endogenous to changes in the distribution of occupational wages.

is a weighted average of the labor supply curves for newly graduated workers for the occupations associated with major d .

In Figure 1, we illustrate what we would expect to occur in response to an increase in labor demand in occupations associated with major d . This demand increase is reflected by the shift from D_0 to D_1 , which increases the expected short-run wage for students who major in d from W_0 to W_1 . In a simple world with no frictions (e.g. transaction costs associated with switching majors, university capacity constraints,⁵ etc.) and perfect information, we would expect some students to respond to this higher wage by switching to major d . This increase in the supply of persons with training in major d increases the labor supply to occupations associated with major d , thereby shifting out the short-run labor supply curve from SRS_0 to SRS_∞ as t goes to infinity. In the long-run, this increased supply drives wages down from W_1 to W_∞ , and the long-run supply curve is shown by the dotted line labeled “LRS.”

[Insert Figure 1 here]

If the long-run labor supply curve is perfectly elastic, this increase in labor supply would return wages to W_0 . However, lack of perfect information or frictions in labor supply – such as if there are university capacity constraints or if some students lack the skills necessary to be successful in a particular major (and recognize this) – will yield a LRS with a positive slope. In this case, the demand shock translates into a permanent income shock. In particular, there may not be enough persons with the requisite talents, skills, or interest to be motivated to switch to major d despite the persistent increase in wages for major d ’s associated occupations.⁶ The thick line with arrows on Figure 1 reflects the expected time path of wages moving from W_0 to the long-run W_∞ .

The persistence of the initial shock to wages will be affected by both the speed and extent of the labor supply increase shown in Figure 1 as well as by the persistence of the demand shock

⁵ For example, it is argued that a shortage of nursing faculty thwart some students from pursuing undergraduate degrees in nursing (American Association of Colleges of Nursing, 2009).

⁶ For example, a student with very little mathematical skill will have little opportunity to successfully respond to an increase in wages for physics majors, and future cohorts may not be capable of increasing their own mathematical skills to respond to the shock in the long term. 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 being an English major, and a student with a deep personal curiosity about power and society may prefer the experience offered by being 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. See Goldin and Katz (2008) for a broader discussion of why we might see persistent wage premiums in some fields.

that led to the initial increase in wages. We test whether we actually find persistence in wage shocks, suggesting that students have reason to respond to them, by calculating wage impulse response functions (IRFs) for the 30 majors with the largest enrollments.⁷ The degree to which wage shocks can be treated as persistent or permanent is reflected in these IRFs in Figure 2.

The mean IRF, which is shown by the thick line, shows that a wage shock in year t is more than 50% eroded by year $t+5$ and 80% eroded by year $t+10$ for a typical major. In effect, what we find is that at the mean, there is not sufficient “crowding out” to totally cancel out a wage shock even after ten years, suggesting that students interested in increasing their lifetime income would be able to do so by responding to wage shocks, in accordance with our theory as presented in Figure 1.

[Insert Figure 2 here]

The persistence of wage shocks suggests that students interested in maximizing their financial well-being should consider them when making college major decisions. Yet students face several difficulties in responding to wage shocks. For instance, as is clear from the IRFs across different majors in Figure 2, there is substantial variation across majors. Some majors show 50% or greater persistence by year $t+10$ and some majors show no persistence by year $t+10$. In fact, students face several *substantial* hurdles in making a reasonable forecast of this time path, effectively calculating the IRFs above, and deciding how to respond to it. First, they would need to be aware of the strength of the connection between major d and each occupation. Second, they would need to be aware that wages have risen in occupations associated with major d , the magnitude of that increase, and the duration of the labor demand shock prompting the change in wages. Third, they would need to estimate long-run wages W_∞ by forecasting the speed and size of the response to the wage increase made by other students. Fourth, they would need to estimate the labor demand elasticity for each associated occupation. Fifth, they would need to discount this future time path to arrive at the present value of the wage increase for major d . These sources of uncertainty – both econometric uncertainty and the uncertainty associated with the complexity of the problem – have significant implications for the structure of the choice problem faced by the student (Altonji, Blom, and Meghir, 2012).

⁷ To compute these IRFs, we computed the major’s wage (using the methods and data we describe below) and ran a vector autoregression of W_t on three lags (W_{t-1} , W_{t-2} , and W_{t-3}).

Generally speaking it is quite difficult to forecast future labor demand and earnings. Even the U.S. Bureau of Labor Statistics' forecasts for occupational labor demand in year $t+10$ have been shown to have large errors (Steckler and Thomas, 2005). Given that this type of forecasting is difficult for trained econometricians, we are skeptical that students are accurate in estimating the implications of wage shocks for their own future income prospects. And owing to the daunting complexity of the decision problem faced by the student, we do not compute the equilibrium number of students who *ought* to respond to the wage increase assuming that they had perfect foresight, as we do not believe it is reasonable to expect such perfect foresight. Nonetheless, we believe that it is reasonable to think that they are influenced to some unknown degree by changes in wages associated with major d , and it is our goal to estimate the extent of this response. We also suggest that responses may be stronger when information is more readily available.

Up until recently there was not a great deal of direct labor market information available to help inform students about the economic consequences of the college majors they choose. Popular media has begun to provide this sort of information, but even this information can be contradictory and is likely to be somewhat confusing for students trying to be well informed. To illustrate, we compiled data from three media outlets that highlighted “top-10 occupations for the future”: 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 2010.⁸

Much of the information from these news sources would be difficult to use to make a decision - some of the occupations were specific enough that they mapped to only one major (e.g., “Biomedical Engineer”), but others mapped to many majors (e.g., “Engineer” which includes 92 separate 6-digit CIP majors⁹). Some of the listed “hot occupations” provide little connection at all to college majors. The researcher’s 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. Further, there was not a high degree of correspondence across the three media sources in the occupations that they highlighted in a given year, or stability in their suggestions

⁸ USNWR provided an unranked list of the Top-30 occupations in 2009. CNN reported “Top 10 degrees in demand” rather than occupations in 2004. 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.

⁹ As defined by the U.S. Department of Education’s “Classification of Instructional Programs” (CIP) coding.

across years. For example, in 2008 a total of 18 distinct occupations were highlighted on CNN's and WSJ's Top-10 lists and 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. Across the three years examined, 85 distinct occupations were highlighted out of a maximum possible 140. In short, this synopsis suggests that the media's coverage of hot occupations does not provide consistent or terribly useful information to inform a student's college major decision.

Studies which investigate the information that college students actually have about wages reflect the difficulty in gathering this information. Perceived wages are linked to student choice, but student estimates of wages for particular majors and for college in general are typically imprecise and/or inaccurate (Betts, 1996; Wiswall and Zafar, 2011). Student estimates are found to be fairly accurate when seniors predict wages for their own major; students appear to learn the most about future wages for a major they have already committed to, after it is likely too late to switch (Botelho and Pinto, 2004; Arcidiacono, Hotz, and Kang, 2011; Zafar, 2011).

Access to more usable information about wages has, however, improved of late. Specifically, the inclusion of a field of study variable in the ACS data beginning in 2008 allows a more rigorous public presentation of wages by detailed major, with the report by Carnevale et al. (2012) receiving wide news coverage (e.g., National Public Radio, 2013). Payscale.com has also become a source of information about the wages associated with different college majors (based on their users' data input).¹⁰ These sources of data provide more usable information to students and could make it easier for them to respond to wage changes.

The connection between the information students receive about occupational wages and their college 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. acquaintances or 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.

¹⁰ 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).

Additionally, as we stress above and show below, while some majors are tightly linked to particular occupations, others are not.¹¹ Our hypothesis is that students will be more responsive to changes in wages when the major has tighter connections to particular occupations as this lowers the information hurdle facing students. Finally, we hypothesize that majors with larger average enrollments may be more responsive to changes in wages as students will have a higher likelihood of knowing someone in the labor force who has graduated in these majors, and there may be more university staff servicing these majors who are able to provide better information to students.

3. Literature 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. A significant amount of empirical evidence suggests that earnings potential affects individuals' choice of occupation (e.g. Berger, 1988; Boskin, 1974; Siow, 1984; Willis and Rosen, 1979; Zarkin, 1985). There is less definitive evidence on the extent to which lifetime earnings considerations factor into college major choices, though, as suggested above, it is clear that there are significant differences in earnings according to one's major (Carnevale et al., 2012), and 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).

Empirical evidence tends to suggest 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), field-specific aptitudes (Arcidiacono, Hotz, and Kang, 2012; Stinebrickner and Stinebrickner, 2014; Freeman and Hirsch, 2008), 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).

Work that focuses on connecting field of study to potential future earning generally relies on strong forecasting assumptions. Berger (1988), for instance, estimates the relationship

¹¹ As Boudarbat and Chernoff, (2009) show, a significant share of workers are employed in jobs that are not closely aligned with their educational specialization, though this varies from field to field.

between a college student's predicted future earnings and choice between five broad fields of study. In models that attempt to correct for self-selection bias, assuming individual ability 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 primarily driven by non-pecuniary factors.

The research in this paper is closest in spirit to Boudarbat and Montmarquette (2007) who, as we do, assume that college students from a particular cohort base their decisions 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 suggest 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. We do *not* assume that students have perfect foresight of the future timepath of wages for each major at the time of their major choice. Rather, we assume that students' college major choices are influenced by wage information that is received *during or before* their college career, which students respond to because there is some permanence in wage shocks. When wages change, students update their expectations about future wages for each major, but their individual forecasts of future wages may not be perfect. Second, unlike prior studies, including all of those cited above, we estimate the relationship between college major and labor market earnings using detailed definitions of college majors and related occupational earnings, rather than using a small number of aggregated categories. Using detailed majors allows us to assess whether the relationship between wages and completed majors varies according to the tightness of the mapping between major and occupation, or the size of the major. Third, we utilize a relatively long longitudinal panel of wage and major choice information so that we can evaluate the types of labor market information college students appear to respond to, e.g. the time gap between occupational fluctuations in wages and college choices, and the wages of individuals of different ages. Fourth, 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.

Finally, we are able, using the data from Washington state, to assess the degree to which there are heterogeneous responses to information according to student's prior academic achievement, gender, and race/ethnicity. Some students might, for instance, have better information about the labor market, place a greater weight on future wages, or have more flexibility to alter their college major trajectories, all of which would be expected to influence responsiveness.

4. Methods

4.1. National Analysis

We begin by testing our hypothesis that wages in prior years have a causal effect on completed majors in year t , using a Granger (1969) test. We test whether wages 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:

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

A Wald test is conducted to assess the hypothesis that the gamma coefficients are jointly zero. We run these regressions for each of 36 major groups at the 2-digit level of CIP codes and for 1,062 6-digit majors.¹² 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.

Our second analysis evaluates the strength of the connection between wages and majors and the lag time between the two. For this analysis, we calculate the correlation of the share of all degrees completed in discipline d in year t with the relative wages of discipline d in year $t-y$. Figure 3 illustrates this computation for Registered Nurse Training (which we will hence just call "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

¹² As an example of what these 2- and 6-digit majors include, "Engineering" is a 2-digit major group which spans many 6-digit majors including "Structural Engineering," "Laser and Optical Engineering," and "Chemical and Biomolecular Engineering." For details, see <https://nces.ed.gov/ipeds/cipcode/Default.aspx?y=55>.

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 $t-6$, $t-5$, ..., and $t-1$.¹³ As shown in the note at the bottom of Figure 3, 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 3 here]

We conduct this same correlation computation for each of 36 major groups at the 2-digit level and each of the 1,062 different majors at the 6-digit CIP level. 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 (1) randomly shuffle 1983-2012 wage histories across majors (e.g., the wage history of nursing may be randomly allocated to psychology), (2) compute the weighted average correlation of wages and major share that emerges from this random shuffle, (3) repeat steps 1 and 2 100 times, and (4) compute the standard deviation of the weighted average correlation produced in these 100 iterations.¹⁴ To further show the strength of these relations, we run the following regression for each discipline, with wages measured with various lags y , 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 . 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. Using the actual pattern of occupational employment by major as found for ACS survey respondents in the years 2009 to 2011, we find the share of major d individuals who work in

¹³ Since we are simply evaluating the relationship between completed majors in year t and wages of associated occupations in a *prior* year rather than attempting to estimate the short-run or long-run labor supply curve shown in Figure 1, we do not face the typical identification problem when one tries to estimate a labor supply curve.

¹⁴ 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).

occupation o and set this share as the weight when computing the weighted average wages for major d in year t .¹⁵

To assess whether students are more responsive to wages in majors that have tighter connections to particular occupations; we compute 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).¹⁶ We split the sample of majors into quartiles based on IQV and estimate the correlations described above for the top-quartile, second-quartile, and bottom half of majors. The IQV measurement appears to match common perceptions of what it means to have a tight or loose connection between majors and occupations. For example, among the "tight" majors are many job-targeted fields, such as Petroleum Engineering (IQV of .646) and among the "loose" majors are many more general fields such as Geography (IQV of .985). And, consistent with this, there is a strong negative correlation (-0.51, p -value<0.001) between the major's IQV score and the standard deviation of the major's wages. That is, majors that are tightly connected to particular occupations have wages that are more highly variable across time. This result should not come as a surprise as majors with looser connections are drawing wages from many occupations and averaging across these occupations yields more stability.¹⁷ As a result, for tightly connected majors there is more variation in wages to which students can respond. Thus, there are two reasons why it may be easier to observe changes in wages for majors that are more tightly connected to particular occupations; (1) they present less of a challenge for students to gather information on likely

¹⁵ Note that this 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. An unavoidable limitation of this approach is that we are implicitly assuming that this mapping has remained constant over time. Unfortunately, the ACS only recently began collecting information on college majors. Other data sources (e.g., National Longitudinal Survey of Youth) do not have large enough samples to yield an accurate major-to-occupation mapping at the detailed level. As an alternative method, we used the major to occupation crosswalk developed collaboratively by the National Center for Education Statistics and the Bureau of Labor Statistics (NCES/BLS, 2011) and found similar results (which are available in our working paper (Long, Goldhaber, and Huntington-Klein, 2014)).

¹⁶ 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.

¹⁷ Note that measurement error in wages is likely to be more of an issue for majors with tighter connections to particular occupations as the wage for that major will be based on fewer occupational wage estimates. Thus, if there is such heterogeneity in measurement error across these samples, it would tend to bias downward correlations estimated for the majors with the tightest connections.

wages as there are fewer occupations for which the student needs to track, and (2) they have more wage variation which makes shifts in wages more apparent.

Finally, to assess whether students are more responsive to wages in popular majors, we restrict the sample to the largest majors that, respectively, enroll 90%, 75%, and 50% of total enrollment, and estimate the correlations described above for these restricted samples.

4.2. *Washington State Analysis*

Our second analysis is designed to assess the degree to which more localized local labor market information might influence college students' choice of major, and whether there is heterogeneity in the response to this information. Specifically, we analyze the likelihood of degree completion by 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 2-digit disciplines¹⁸ in response to changes in discipline-specific wages, we use the following alternative-specific conditional logit:

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

p_{diut} is the likelihood of student i in university u completing 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:

$$(3) \quad W_{dut-y} = \frac{\text{wages for discipline } d \text{ at university } u \text{ in year } t-y}{\text{wages for discipline } d \text{ at university } u \text{ averaged across all years}}$$

As an example, suppose that in year $t-y$, mean wages for those who graduated from university u with a degree in Engineering are 10% higher than mean wages for Engineering graduates at the

¹⁸ Several two-digit CIP codes are not used because no college in the sample offers a bachelor's degree in that major group. We conduct this analysis at the 2-digit level because at a finer level the number of observations for many of the majors gets too small, and using a 6-digit level would be computationally challenging as it would require the estimation of many thousands of coefficients, with one coefficient for each student characteristic control variable multiplied by the number of choices.

same university in a typical year. The relative wage measure in (3) would then be 1.10, and we would expect a corresponding shift towards majoring in Engineering.

Returning attention to Equation 2, X_i is a vector of demographic variables including gender, race (non-Hispanic white, non-Hispanic black, non-Hispanic Asian, and Hispanic), ethnicity, age and age squared, dummies indicating high, low, or missing entrance exam scores,¹⁹ and dummies indicating FRPL status in high school. FRPL data is available for virtually all students who attended high school in Washington State, so indicators of missing FRPL status is included as a proxy for students who are enrolled in Washington institutions from out of state. U_u is a vector of university dummies to capture non-wage 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: 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 lags of $t-3$, $t-2$, and $t-1$. In all cases, marginal effects are calculated using simulation by adding 0.01 to W_{dut-y} , computing Δp_{diut} , and then multiplying this change by 100.

To evaluate the possibility of heterogeneity in responses, we allow the response (i.e., β) to vary by adding, to the specification shown in Equation 2, interactions of W_{dut-y} with gender, race, test scores, and FRPL status.²⁰ To compute marginal effects for each subgroup, we add 0.01 to W_{dut-y} , and compute the mean of $100 \times \Delta p_{diut}$ for each subgroup. To obtain the standard error for this mean marginal effect, we use a bootstrapping approach, by computing the mean marginal effect for each subgroup for each of 100 bootstrapped samples (each sample consisting of $0.5 \times N$ observations) and then computing the standard deviation of these 100 mean marginal effects.

¹⁹ A "high" score is above 1000 on the combined math and reading SAT exams. If SAT scores are not reported but ACT scores are, the equivalent ACT score of 22 or above on math and reading is used (ACT, 2014). A dummy for no reported entrance exam score is also included.

²⁰ We drop the campus fixed effects in this analysis as the added interaction terms make model convergence more difficult. In results not shown, we obtained relatively robust results for the non-interacted specification when we included or excluded campus fixed effects.

Finally, we compute difference in the mean marginal effects across subgroups (e.g., mean marginal effect for females minus the mean marginal effect for males), and to generate one-tailed p-values for the difference in mean marginal effects, we count the number of iterations out of 100 in which group 1 had a larger mean marginal effect than group 2.

5. Data and Empirical Counterparts

5.1. *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), collected by the U.S. Department of Education. Since CIP codes have changed periodically over time, we crosswalk all 6-digit codes to their 2000 values using the crosswalks supplied by NCES (2013).²¹ The IPEDS data is then collapsed by year to compute the total number of degrees produced in each 6-digit CIP, and these totals are then converted into shares for year t . We then collapse these shares to the 2-digit CIP level.

5.2. *National Data on Wages*

The data on wages by occupation for the years 1983 to 2012 are taken from the Current Population Survey's (CPS) Merged Outgoing Rotation Groups using the extracts provided by the National Bureau of Economic Research (2013). We define occupations using 3-digit SOC codes. These SOC codes have also changed periodically over time, thus we use the "proposed standard code" in Appendix A of Meyer and Osborne (2005) to crosswalk these codes.²² For each of these occupations, we compute the average of weekly earnings (weighted using an individual's "earnings weight" as provided by the CPS). 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 .

5.3. *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 2012.²³ Students' administrative records and demographic characteristics are matched to

²¹ 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.

²² 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.

²³ 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.

Unemployment Insurance (UI) data that includes students' wages after graduation.²⁴ Our sample includes 58,511 students who graduated with a bachelor's degree between fall 2007 and spring 2012.

The earned wages associated with a particular discipline d in time t at university u is the mean first-year total wages of all students who graduated with a bachelor's degree in d from university u in academic year t . For our alternate wage measures, we instead use mean first-year total wages of all students who graduated with a bachelor's degree in d from any of the eight public Washington universities in academic year t using UI records; CPS estimates of average weekly earnings of Washington workers with bachelor's degrees working in occupations associated with discipline d ; or CPS estimates of average weekly earnings of U.S. workers with bachelor's degrees working in occupations associated with discipline d .

The correlation in CPS and ERDC-derived wages is statistically significant, but small (0.078). This low correlation between CPS and ERDC-derived wages could result from the differing age groups in the two samples or other sampling characteristics. For instance, ERDC wages are based on recent college graduates only, while CPS wages look at a wider range of bachelor's degree holders, and ERDC wages look only at those who graduated from Washington public four-year colleges, while CPS covers bachelors' degree holders from private colleges, out-of-state colleges, and community colleges as well. The low correlation may be owed to a labor market segmented along lines of age, college quality, and between-state migrant status (Reich, Gordon, and Edwards 1973).

Annual earned wages based on the first of these wage definitions vary 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 7 and 14 percent of wage variation. Seventy-two percent of the wage variation is unexplained by discipline, campus, or year.

When the mean wage is computed using the second wage definition (i.e., based on recent graduates of any of our eight public Washington universities), it becomes easy to see the stark differences between annual earned wages paid to graduates from different disciplines. Figure 4

²⁴ Students are linked to UI wage data using the Social Security Number provided in their baccalaureate records. UI wage data does not include those who are self-employed or those employed by the military, but since this is likely a small percentage of those with recent bachelor's degrees, their omission is not likely to significantly bias wage means.

illustrates full-sample mean wages for ten disciplines over the sample period. Earned wages differ strongly by field of study. In a given year, the standard deviation in wages between the disciplines each year is about \$8,000. Those with computing and information services degrees and health-related degrees earn the most, with first-year earnings of about \$45,000 per year. Most disciplines receive earnings below \$25,000 per year, and the least lucrative degrees, history, communications, and foreign language, offer first-year earnings of \$16,000-\$17,000 per year.

[Insert Figure 4 here]

6. Results

6.1. National Analysis

Table 1 summarizes the results of our tests that prior wages in discipline d Granger-cause bachelor's degrees in d in year t . Wages are found to significantly Granger-cause majors for more than three-quarters of all majors when measured at either the 2- or 6-digit level. The weighted average p-value of the test of Granger-causality is 0.040 for the 36 2-digit majors and 0.104 for the 1,062 6-digit majors. About 80% of all majors show a statistically significant correlation at the 95% level.

[Insert Table 1 here]

Table 2 shows the strength of the relationships between the awarding of bachelor's degrees in major d in year t and wages in major d in year $t-y$. The estimated correlations are slightly larger at the 2-digit level than at the 6-digit level, with the peak correlations being 0.207 at $t-1$ for 2-digit major groups and 0.140 at $t-3$ for 6-digit majors.²⁵ Squaring the peak 6-digit 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 6-digit major d in year $t-3$ on the share

²⁵ We also explored the correlations of wages and majors at an even more aggregated level, with majors grouped into four categories: STEM (i.e., Science, Technology, Engineering, and Math); Humanities, Social Sciences, and Other). Our reason for exploring more aggregated categories is that the prior literature used more aggregated groups. Boudarbat et al. (2007) grouped majors into 7 groups (Education; Fine Arts and Humanities; Social Sciences; Commerce Business; Agriculture and Biological Sciences; Health; and Sciences), while Beffy et al. (2012) used 3 groups (Sciences; Humanities and Social Sciences; and Law, Economics, and Management). Averaging across our four major groups, the peak correlation of wages and majors was 0.154 at $t-1$. These results are not shown, but are available from the authors.

of bachelor's degrees going to major d in year t is 0.014.²⁶ 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 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 0.67. Whether this response is large or small is in the eye of the beholder. We would characterize this level of responsiveness as “modest”. We find a smaller percentage point effect, but larger elasticity than Beffy et al. (2012) who, as we note above, estimate the relationship between earnings and majors using a fundamentally different approach applied to French students. 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. Yet, since they are evaluating relationships using aggregated major groups that have larger initial shares, the corresponding elasticities are far smaller (0.09, 0.14, and 0.12, respectively) than our estimated elasticity of 0.67. They characterize their results as “quantitatively small even though they are statistically significant” (p. 342), and we largely share this conclusion.²⁷

[Insert Table 2 here]

Given the result in Table 1 that degree production responds significantly to wages in about 80% of majors, it is natural to ask what separates majors with strong responses from those without. Table 3 shows strong evidence supporting our hypothesis that students are more responsive to wages in majors that have tighter connections to particular occupations. The peak correlation between wages and majors is 0.345 for majors in the top-quartile, 0.238 for majors in the 2nd quartile, and only 0.096 ($p > 0.10$) for majors in the bottom-half of the distribution (i.e., those majors with the loosest connections to particular occupations). When evaluated as elasticities, the differences are striking. For majors whose connection to particular occupations

²⁶ These regression results are not shown, but are available from the authors.

²⁷ As shown in our working paper (Long et al., 2014), we find similar results for “all degrees” as we find for bachelor's degrees. We also explore whether the results are stronger when computing wages based on samples of CPS workers restricted to (1) only those aged 30 and under, (2) only those with a bachelor's degree, or (3) both restrictions. Our theory was that 4-year college students may be more responsive to the wages earned by individuals with a bachelor's degree and/or to 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. Yet, we find no evidence of stronger correlations.

is highest (i.e., in the top-quartile), the estimated elasticity of these majors with respect to their wages lagged three years is 2.35; a 10% increase in wages for these majors would raise their average major's share from 1.85% to 2.34%. This estimated responsiveness is three-and-a-half times the size of the estimated elasticity for all majors (0.67), and we would characterize this response as “large”. The peak elasticities fall monotonically as we move to majors progressively less connected to occupations: 1.89, 0.65, and 0.05, respectively for the 2nd, 3rd, and 4th quartile.

[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. In Table 4 we report model specifications that test this hypothesis. 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, thus these models fail 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]

6.2 Washington State Analysis

Table 5 displays student response to wages in the Washington State sample. Each reported coefficient and average marginal effect is from a separate analysis. 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 (0.022 with respect to recent graduates of the student's own university and 0.026 with respect to recent graduates from any of the eight universities in our data). A marginal effect of 0.022 suggests that if a major saw its wages rise 10% more than other majors' wages in year $t-3$, then the share of students completing that major in year t would increase by 0.22 percentage points. We would characterize this average response as modest, but also strikingly similar to the magnitude we find in the national analysis.

[Insert Table 5 here]

In general, the results in Table 5 suggest that students are more responsive to localized data; we, for instance, see the far larger student major responses when using either wages from

prior students from their own university (column 1) or Washington State universities (column 2) than when using wages from a broader segment of workers in Washington (column 3) or national wages (column 4).

It is unclear whether the responsiveness to the “localness” of labor market information shown in Table 5 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).

Table 6 shows how the marginal response to changes in wages differs for various student subgroups. For this analysis, we look at responsiveness to wages of graduates of the student’s own university in year $t-3$. The first marginal effect shown on Table 6, which is 0.22 for all students, is simply a repeat of the result shown in the first column of Table 5. Below this, we show how this marginal effect varies. We find that males respond substantially more to changes in major-specific wages than females (0.033 versus 0.013), which is consistent with the findings of Boudarbat and Montmarquette (2007) that in general men respond more strongly than women to initial earnings. We also find that black students respond less than white students (0.022 versus -0.005). By contrast, there is little evidence of differences in the responsiveness based on students’ FRPL status, whether they come from out of state, or based on SAT test score.

[Insert Table 6 here]

7. Conclusions

In this paper we find that students’ choice of major responds positively to longitudinal changes in relative wages. We characterize the average response as modest, but generally consistent with other work investigating the connection between labor market earnings and college major choices (e.g. Beffy et al., 2012). This result is not terribly 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 lead to well-informed responses. Information about earnings associated with particular majors is sparse, and generally relegated to academic studies. Information about earnings based on occupations is more readily available, and increasingly so,

but students attempting to use this information face another stumbling block: occupations are often linked to many majors and vice-versa. Consequently, students have to make assumptions about the mapping of majors into occupations and track the wages associated with a wide range of outcomes.

However, looking at student response to wages in detail, we find heterogeneity in the response. Given the difficulty in tracking wages and observing the labor market, perhaps it is not surprising that students are more responsive to wage changes in majors that are closely associated with particular occupations. While the supply response for the average major has an elasticity of 0.67, a tightly-connected major has an elasticity of 2.35.

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. Interventions which aim to improve student responsiveness to labor market cues with information provision alone run into a problem in that student responsiveness to the labor market is modest to begin with. These interventions would also need to take into account the timing of information; we find that students respond most strongly to wages observed when they are approximately freshmen.

An informational intervention alone would need to either substantially improve students' information about labor market returns to majors or increase students' responsiveness to such information in order to lead to yield results considered adequate by policymakers.

However, better quality information or additional institutional emphasis on the labor market may still increase student responsiveness to labor market cues. We do find that students respond more strongly in cases where information is more salient and applicable. By making information more salient and applicable, it is possible that student response could rise further. In addition, certain groups, in particular women and black students, do not respond as strongly as other students. We cannot say whether this differential response might be related to heterogeneous preferences, the wage information that is received by these subgroups of students, or their ability to respond to wage information while in college. These issues merit further investigation given that occupational choices that will be influenced by college majors help explain some of the wage gaps that exist in the workforce.

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Figure 1: Demand for and Supply of Labor in Occupations Associated with Major d , and the Weighted Average Equilibrium Wage and Labor in These Occupations

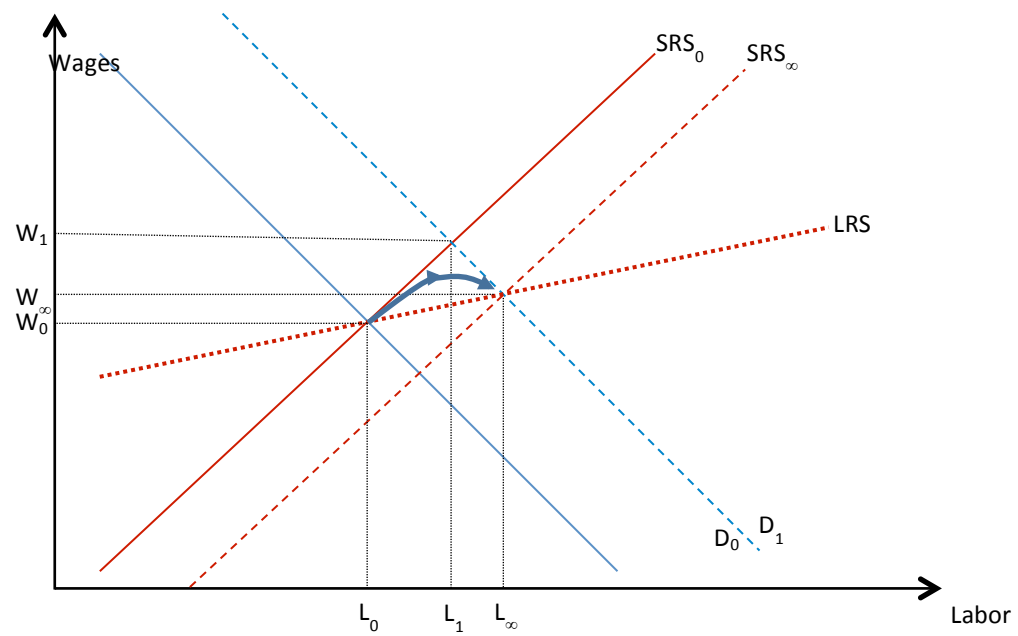
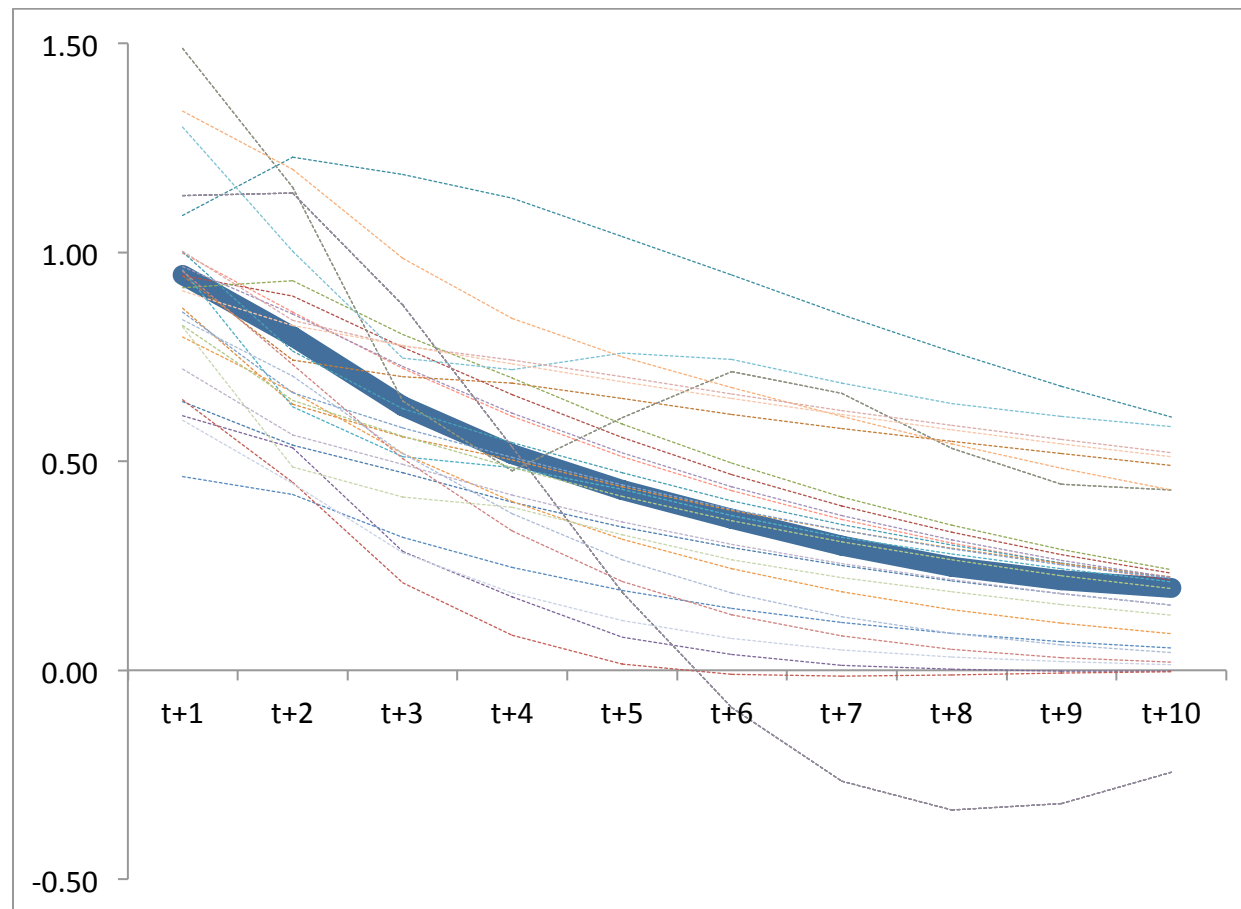


Figure 2: Wage Impulse Response Functions for the 30 Most Popular Majors



Note: The thick line reflects the mean of the 30 individual impulse response functions.

Figure 3: Wages and Share of Bachelor's Degrees in "Nursing" (i.e. Registered Nurse Training)

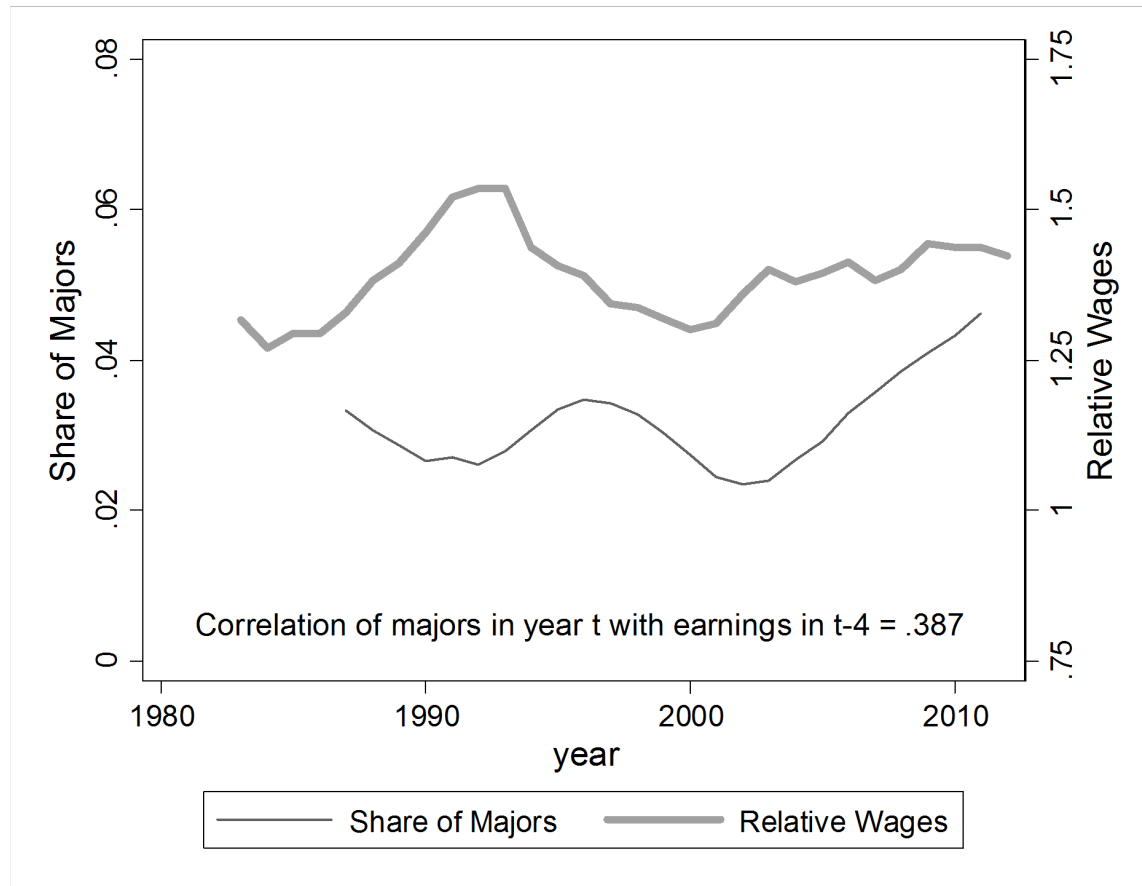


Figure 4: Mean First-Year Wages in Ten Selected Disciplines over Time

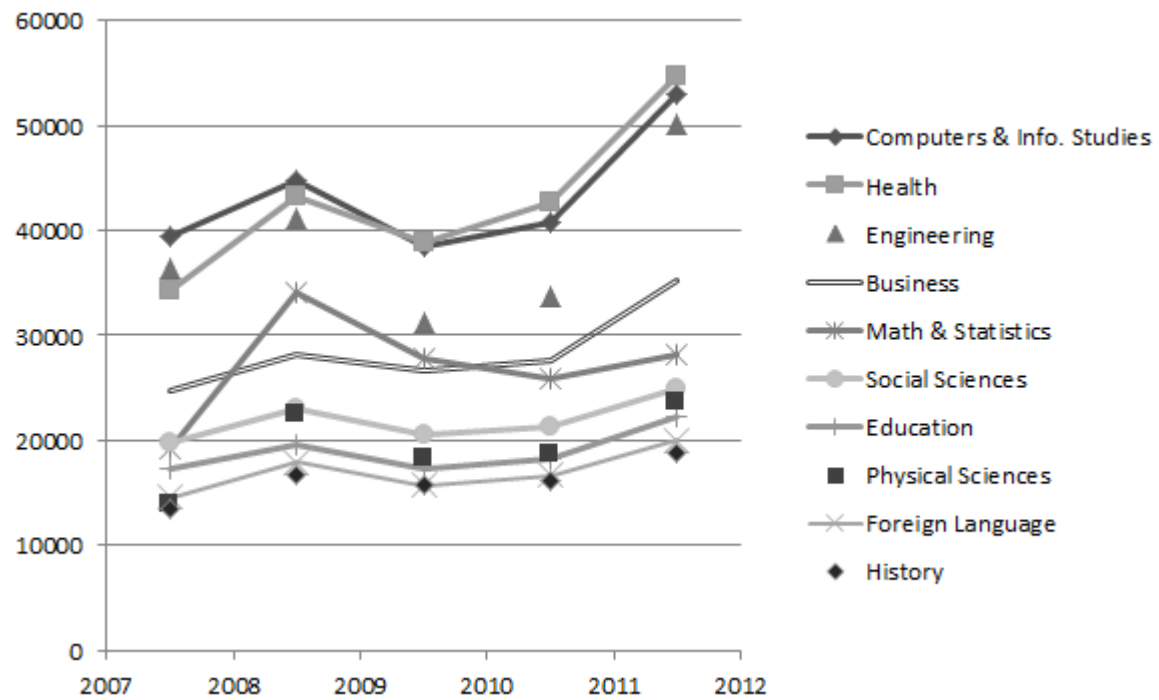


Table 1: Does Wages in Years $t-1$ to $t-6$ Granger Cause Majors in Year t ?

	CIP Code Level:			
	2-Digit		6-Digit	
<i>Weighted Average P-Value</i>	0.040	**	0.104	+
<i>Total Majors Evaluated</i>	36		1,062	
<i>Majors with P-Value ≤ 0.1</i>	32 (89%)		899 (85%)	
<i>Majors with P-Value ≤ 0.05</i>	29 (81%)		840 (79%)	
<i>Majors with P-Value ≤ 0.01</i>	28 (78%)		721 (68%)	

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 2: Correlation Between Majors Produced in Year t and Associated Occupational Wages in Year $t-y$

Wages Measured in Year:	CIP Code Level:			
	2-Digit		6-Digit	
$t-1$	0.207	**	0.111	**
	(0.092)		(0.048)	
$t-2$	0.206	**	0.130	***
	(0.097)		(0.049)	
$t-3$	0.199	*	0.140	***
	(0.103)		(0.051)	
$t-4$	0.175	*	0.135	***
	(0.101)		(0.051)	
$t-5$	0.150	+	0.132	***
	(0.095)		(0.051)	
$t-6$	0.110		0.116	**
	(0.087)		(0.050)	

Note: Standard errors of the correlations are in parentheses.
 ***, **, *, 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 Majors and Wages Higher for Majors with "Tighter" Connections to Particular Occupations?

	(1)		(2)		(3)	
Connection of Major to Occupations	Tightest: Top-Quartile		Tightest: 2nd-Quartile		Loosest: Bottom-Half	
Wages Measured in Year:	Correlation (S.E.)					
<i>t</i> -1	0.222 (0.092)	**	0.142 (0.092)	+	0.064 (0.057)	
<i>t</i> -2	0.276 (0.104)	***	0.175 (0.092)	*	0.081 (0.060)	
<i>t</i> -3	0.308 (0.115)	***	0.214 (0.090)	**	0.096 (0.059)	+
<i>t</i> -4	0.336 (0.123)	***	0.232 (0.086)	***	0.088 (0.058)	+
<i>t</i> -5	0.345 (0.125)	***	0.238 (0.082)	***	0.089 (0.057)	+
<i>t</i> -6	0.328 (0.121)	***	0.228 (0.081)	***	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.

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 (S.E.)						
<i>t</i> -1	0.111	**	0.103	**	0.106	*	0.106 *
	(0.048)		(0.049)		(0.063)		(0.063)
<i>t</i> -2	0.130	***	0.118	**	0.121	*	0.121 *
	(0.049)		(0.050)		(0.064)		(0.064)
<i>t</i> -3	0.140	***	0.124	**	0.127	*	0.127 *
	(0.051)		(0.052)		(0.066)		(0.066)
<i>t</i> -4	0.135	***	0.115	**	0.116	*	0.116 *
	(0.051)		(0.051)		(0.066)		(0.066)
<i>t</i> -5	0.132	***	0.108	**	0.106	*	0.106 *
	(0.051)		(0.050)		(0.064)		(0.064)
<i>t</i> -6	0.116	**	0.084	*	0.079		0.079
	(0.050)		(0.049)		(0.062)		(0.062)

Table 5: Does Students' Choices of Majors Respond More to Wages Received by Recent Graduates in their State?

	(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:	Coefficient (S.E.) [Average Marginal Effect]						
<i>t-1</i>	0.071 (0.040) [0.003]	*	0.134 (0.079) [0.006]	*	0.286 (0.082) [0.011]	***	-0.346 (0.370) [-0.014]
<i>t-2</i>	-0.062 (0.053) [-0.003]		-0.187 (0.092) [-0.008]	**	0.043 (0.066) [0.002]		0.383 (0.333) [0.015]
<i>t-3</i>	0.518 (0.111) [0.022]	***	0.625 (0.188) [0.026]	***	0.115 (0.061) [0.005]	**	0.349 (0.318) [0.014]

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 6: Heterogeneity in the Response of Students' Completed Majors in Year t to Local Labor Market Wages in Year $t-3$

Student Group	Marginal Response		Student Group	Marginal Response	
<i>All Students</i>	0.022 (0.002)	***			
<i>Males</i>	0.033 (0.003)	***	<i>Non-FRPL Recipient</i>	0.023 (0.003)	***
<i>Females</i>	0.013 (0.003)	***	<i>FRPL Recipient</i>	0.021 (0.005)	***
<i>Difference (F – M)</i>	-0.020	***	<i>Missing FRPL Status (Out of State Students)</i>	0.022 (0.003)	***
<i>Non-Hispanic Whites</i>	0.022 (0.002)	***	<i>Difference (FRPL – Non)</i>	0.002	
<i>Non-Hispanic Blacks</i>	-0.005 (0.011)		<i>Difference (Miss – Non)</i>	0.001	
<i>Non-Hispanic Asians</i>	0.021 (0.002)	***	<i>SAT Score Above 1000</i>	0.021 (0.003)	***
<i>Hispanics</i>	0.022 (0.002)	***	<i>SAT Score Below 1000</i>	0.017 (0.004)	***
<i>Difference (B – W)</i>	-0.028	**	<i>Missing SAT Score</i>	0.020 (0.003)	***
<i>Difference (A – W)</i>	-0.001	*	<i>Difference (Low - High)</i>	-0.004	
<i>Difference (H – W)</i>	0.000		<i>Difference (Miss - High)</i>	-0.001	

Note: Wage data is taken from UI records for recent graduates of eight public universities in Washington State. ***, **, *, and + denote two-tailed significance at the 1%, 5%, 10%, and 15% levels respectively. Standard error of the marginal effect is in parentheses.