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The Changing Importance of Earnings in College
Major Choice
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The Changing Importance of Earnings in College Major Choice

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Abstract

Prior studies find that undergraduate major choices are responsive to earnings associated with those majors, but weakly suggests that responsiveness has dropped over time. Using data on college graduates from 1973 to 2013, we find that responsiveness of major choice to labor market returns has weakened over time. The weakening response is due to changes within demographic groups rather than demographic changes in the college graduate population over time. If the goal is to maintain or increase the alignment between college major and labor market returns, incentivizing undergraduates to select high-earning majors is necessary.

Keywords: Major choice, Consumption value, college major, educational choice

JEL: I23, I26, J24

I. INTRODUCTION

The labor market returns associated with different college majors vary widely ([Carnevale et al., 2012](#); [Altonji et al., 2016](#)). The gap in average earnings between majors is comparable to the gap in average earnings between college graduates and those with only high school degrees ([Carnevale et al., 2012](#)). In this context, there is a common popular narrative that students increasingly choose “worthless” majors - majors that will provide them with a low return on their educational investment.

The determinants of college major choice are varied and involve both financial and non-

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financial considerations. Students may choose a given major because they enjoy the classroom experience that a particular major offers ([Wiswall and Zafar, 2015](#)), because of their comparative skill or likelihood of success in the major or related occupations ([Stinebrickner and Stinebrickner, 2014](#); [Altonji et al., 2016](#)), and/or for reasons of parental encouragement. Of all of the reasons to choose a major, however, labor market returns could be the most consequential for a student’s adult socioeconomic standing. Students who choose less lucrative majors may be unable to easily pay back student loans, which have increased over time ([Chen and Wiederspan, 2014](#)), or they may find themselves with uncertain labor market positions. Financial instability in young adulthood is linked to savings capacity and educational debt, and also has implications for many later life outcomes, such as marriage timing ([Dew and Price, 2011](#); [Addo, 2014](#)). There is thus reason to be concerned if students are disregarding the labor market consequences of their major choice decisions.

Responsiveness of students to potential future earnings associated with major choice is also a matter of interest for institutions of higher education. In light of large differences in earnings returns for different majors, and with some additional public policy preference for STEM fields regardless of their personal financial return, several higher education policies have been proposed or enacted to guide students towards certain majors, often with the stated goal of aligning degree production with the labor market. As [Altonji et al. \(2016\)](#) points out, these policies have moved forward in the United States at the federal level ([Scott, 2013](#)), at the state level in places like Florida ([Alvarez, 2012](#)) and New York ([Chapman, 2014](#)), and at the institutional level ([Stange, 2015](#)).

We, therefore, analyze college major choice elasticity - the extent to which college major choices are responsive to earnings associated with those majors - paying particular attention to changes over time in this elasticity from the 1970s to the early 2010s. We follow the approach of [Long \(2004\)](#), who studies the changing response of student matriculation to tuition over time. We examine samples of bachelor’s degree completers in five nationally representative data sets (NLS:72, NLSY:79, NELS:88, NLSY:97, ELS:2002). Major and

occupation data from these five data sets are connected to the Current Population Survey to construct anticipated labor market returns to majors in each year, and we investigate how student major choice responds to these anticipated labor market conditions. We look at major choice responses to mean and median wages, to inequality in the earnings distribution (using standard deviation of wage and the 90/10 ratio), to the unemployment ratio, and to the concentration of majors within occupations (using a major-occupation Gini coefficient).

Our focus on college major choice elasticity mirrors a growing literature ([Arcidiacono, 2004](#); [Long et al., 2015](#); [Arcidiacono et al., 2011](#); [Boudarbat and Chernoff, 2009](#); [Stinebrickner and Stinebrickner, 2011](#); [Beffy et al., 2012](#), e.g.), which generally finds that the response of major choice to earnings is positive but somewhat weak. This literature does not attempt to estimate how this relationship has changed over time, which is an important question given that much of the policy focus on the labor alignment of major choice is recent and that the demographic makeup of college graduates has changed considerably in recent years as higher education has become more available to groups that were traditionally excluded. Earlier studies of major choice, using data from the 1960s and 1970s, did tend to find somewhat stronger responses to earnings ([Fiorito and Dauffenbach, 1982](#); [Berger, 1988](#); [Montmarquette et al., 2002](#)), but their results are not methodologically consistent with more recent studies and are therefore hard to compare. Understanding the relationship between anticipated earnings and student major choice, and whether policy measures should be adjusted to create better alignment between the two, should rely on an assessment of whether current undergraduate major choice behavior is a new phenomenon or just newly recognized.

We find that the response of major choice to mean and median wages has weakened over the past four decades, with the elasticity reducing sharply and then rebounding, for a beginning-to-end reduction in response to mean and median wages by half. We also show that inequality in the earnings distribution has shifted from being a positive predictor of major choice to a null predictor. The influence of several other predictors - unemployment and the strength of the link between majors and particular occupations - fluctuates from

cohort to cohort but does not follow an obvious time trend. However, these relationships between labor market conditions and major choice were not strong even in the 1970s. Major choice decision-making has thus been typified by a weak response to labor market conditions, and that response has become even weaker over time. We attempt to explain declining responsiveness of major choice to labor market conditions using the major shifts in college graduate demographics across time, but do not find that variations in student demographics are responsible for the change.

II. DATA AND METHODS

For this project, we combine data from five longitudinal data sets with earnings data from the Current Population Survey (CPS) in order to link observed wages in the CPS with major choice in the longitudinal data.

Major choice data is drawn from bachelor’s degree holders graduating in the National Longitudinal Study of the High School Class of 1972 (NLS72, $n=5,778$ subjects born 1950-1956), the National Longitudinal Survey of Youth 1979 (NLSY79, $n=3,189$ subjects born 1957-1965), the National Education Longitudinal Study (NELS88, $n=3,974$ subjects born 1972-1975), the National Longitudinal Survey of Youth 1997 (NLSY97, $n=1,917$ subjects born 1981-1985), and the Education Longitudinal Study of 2002 (ELS02, $n=5,228$ subjects born 1983-1987). These data sets span four decades and allow for changes across cohorts to be tracked. The primary variable of interest we draw from these data sets is the college major with which someone earns a bachelor’s degree.¹ We consider only bachelor’s degree holders in our analysis.²

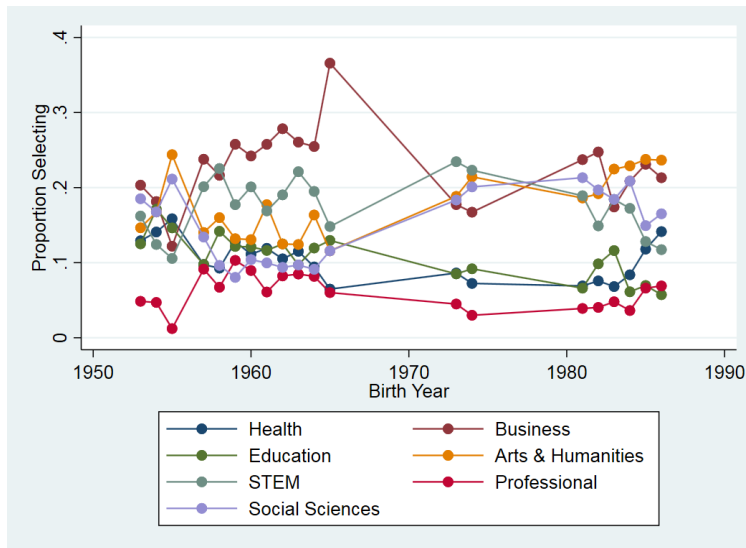
All majors are incorporated into one of seven categories: Health (11.51% across all

¹Double majors, which are rare, are assigned to whichever major is listed first in the data for analyses of major choice. When linking major to occupation, double majors are effectively counted as two people.

²This means that we cannot incorporate differentials in dropout rates across college majors. We do not have data on majors chosen but not completed in most of these data sets.

data sets), Business (20.46%), Education, (10.94%), Arts & Humanities (19.27%), STEM (15.97%), Social Sciences (16.40%), and Professional Programs (5.45%). While this approach loses some detail in the choices made by students, it avoids small cell size issues, handles specific majors that appear or disappear over time, adjusts for differing levels of detail in college major data across data sets, and eases the econometric strain faced by choice models estimated with large numbers of options. For many of these reasons, other studies in the major choice literature also aggregate college major categories (e.g. [Arcidiacono, 2004](#); [Arcidiacono et al., 2011](#); [Beffy et al., 2012](#); [Baker et al., 2016](#); [Hastings et al., 2017](#)). Figure 1 shows the relative popularity of each major category according to birth year. There is significant variation across the sample window in the popularity of each major category.

Figure 1: Popularity of Major Categories by Birth Year



To avoid noisy results from uncommon birth years at the beginning or end of a data set sample, 1956 is reassigned to 1955, 1972 to 1973, 1975 to 1974, and 1987 to 1986.

The focal variable of interest is field of study for bachelor's degree holders, which could potentially be collected from cross-sectional data. However, large cross-sectional data sets for the United States generally do not collect information on college major. Also, longitudinal data allow us to incorporate family background and high school performance characteristics unavailable in cross-sectional data, and to track actual occupations and earnings later in

life. In addition to college major, we collect several characteristics available in all five data sets: gender, race, mother’s education, family income, and high school test score. Because detail of racial categories differs across data sets,³ we reduce racial differences to white versus non-white. Mother’s education is collapsed to four categories: no high school degree, HS degree, some college, and college graduate. Family income and pre-college math and verbal test scores are recorded as quartiles relative to the *entire* sample, including those who do not receive bachelor’s degrees, allowing the analysis to track how the makeup of college graduates relative to the population has changed over time.⁴

Table 1 shows how the demographic makeup of college graduates changes across the five data sets. In this table we see reflected standard stylized facts about changes in the United States higher education system. The proportion of women grows steadily over time, to near 60% in recent cohorts. As the population earning BAs grows overall, we see more students from lower levels in the high school test score distribution. As education levels rise overall, we see the education level of mothers increasing as well. BA holders come increasingly from the higher part of the family income distribution over time, with the exception of the ELS02 sample, which is an outlier in this regard.

In order to estimate the relationship between college major choice at a given point in time and the future labor market consequences related to that choice, it is necessary to estimate future earnings for each college major. There is not a single settled approach to doing so in the literature on college major choice. Students appear to take cues about occupation and major-linked earnings from previous cohorts (Freeman, 1975; Long et al., 2015), and so actual future realized earnings are not ideal. Unfortunately, large-scale data that links current earnings to the field of study of current workers is only available for recent cohorts, such as in the American Community Survey.

³Detail of racial categories differs across data sets; in particular, very few Asian subjects can be cleanly identified in NLS72, NLSY79, and NELS88. In effect, we just compare white to non-white groups.

⁴Test scores are from the ASVAB for NLSY79, NELS88, and NLSY97, and are standardized exams from the researchers for NLS72 and ELS02.

Table 1: Demographics of BA Holders Across Samples

	NLS72	NLSY79	NELS88	NLSY97	ELS02
Female	0.480	0.531	0.565	0.576	0.571
White	0.846	0.709	0.760	0.693	0.667
Family Income					
Quartile 1	0.174	0.118	0.112	0.096	0.183
Quartile 2	0.183	0.189	0.221	0.167	0.152
Quartile 3	0.263	0.264	0.239	0.291	0.394
Quartile 4	0.381	0.430	0.428	0.446	0.271
High School Test Score					
Quartile 1	0.046	0.046	0.046	0.027	0.051
Quartile 2	0.135	0.130	0.145	0.142	0.149
Quartile 3	0.277	0.279	0.294	0.282	0.309
Quartile 4	0.541	0.545	0.514	0.548	0.491
Mother’s Education					
Less than HS	0.142	0.214	0.050	0.085	0.051
HS Degree	0.383	0.442	0.260	0.252	0.185
College, No BA	0.256	0.163	0.240	0.28	0.313
BA or More	0.218	0.181	0.450	0.383	0.451

In this study, we use a two-step approach to estimating future earnings where we link college major to occupation, and then occupation to earnings. This approach follows [Long et al. \(2015\)](#). First, we construct a matrix of weights linking college major to actual future occupation within each data set.⁵ For example, if 10% of Business majors in NLS72 become mid-level managers, and 20% of Business majors in NLSY79 become mid-level managers, then the “mid-level manager” column receives a .1 weight in the “Business major” row of the NLS72 major-occupation matrix, and a .2 weight in the NLSY79 major-occupation matrix.

Then, we use Current Population Survey (CPS) Merged Outgoing Rotation Group data for bachelor’s degree holders between the ages of 25 and 35 from 1968-2016 to calculate unemployment rates and features of the wage distribution (mean, median, etc.) for each occupation in each year. We perform these calculations separately by gender. Finally, we use the major-occupation matrix weights to aggregate together these occupational results,

⁵We use the simplified SOC occupation coding used in NELS88, which lists 39 different occupations, since it is the most general occupation coding among our data sets, and avoids small cell issues.

producing major-year specific anticipated unemployment rates and features of the wage distribution.

We also use the major-occupation matrix to construct a Gini coefficient for each major, measuring how concentrated the graduates of each major are within particular occupations. Majors that are more concentrated within occupations have higher Gini coefficients, whereas majors that are distributed more equally across occupation, have lower Gini coefficients. For example, nursing majors have a strong tendency to become nurses and so the nursing major (used as a hypothetical example here) would have a very high Gini coefficient, whereas history majors head into a wider array of occupations and would have a lower Gini coefficient. Notably, since the major-occupation matrix is constructed at the dataset level, variation in the Gini coefficient is at the major-dataset level, rather than major-year as it is for other variables.

This wage-prediction approach leads to wages that do indeed predict later-life outcomes. We check that this is true by looking at realized wages of students in the sample. We regress their actual log wages at or near age 30 on the log mean wages associated with the major they graduated in at the time they chose their major. The linear coefficient is .602 for NLS72, .828 for NLSY79, .838 for NEL88, and .863 for NLSY97. All four coefficients are significant at the 1% level. We did not test ELS02 because students were not near age 30 at the latest follow-up survey. The relationship between predicted and actual wages is somewhat weaker for NLS72, but is a consistently effective predictor for NLSY79, NEL88, and NLSY97.

With these data in hand, we estimate major choice models using conditional logit specifications. Each model predicts the probability that the student i will choose major m out of the full list of seven, using one feature W_m of the anticipated labor market consequences of choosing that major as a predictor. We use mean wage, median wage, standard deviation of wage, 90/10 ratio, and unemployment.⁶ In practice, results are nearly identical for mean

⁶To avoid unintuitive estimates in the normal-distribution tails of the random effect preference distributions, the effects of mean and median wage on choice are constrained to be positive, and the effect of unemployment is constrained to be negative.

wage and median wage, and for standard deviation of wage and the 90/10 ratio, and so we only present results concerning the mean wage, the 90/10 ratio, and unemployment here.

$$Y_m^* = \beta_{0m} + \beta_1 W_m + \varepsilon_{im} \quad (1)$$

$$Pr(Y_c^* = \max\{Y_1^*, Y_2^*, \dots, Y_7^*\}) = \frac{\exp(\beta_{0m} + \beta W_m)}{\sum_{d=1}^7 \exp(\beta_{0d} + \beta W_d)} \quad (2)$$

where Y_m^* is a latent variable and $Pr(Y_m^* = \max\{Y_1^*, Y_2^*, \dots, Y_7^*\})$ indicates the probability of choosing major m from the list of seven major types. The model is estimated using the hierarchical Bayes (HB) algorithm (Rossi et al., 2005; Sawtooth Software, 2009; Sermas, 2014). The HB algorithm allows the coefficients α_m and β to follow a random distribution over the students correlated with a set of individual characteristics X_i , which include gender, white/nonwhite status, and indicators for family income quartile, standardized test score quartile, mother's education, and data set.

$$\beta_{0c} \sim N(\gamma_{0c} + X_i \delta_{0c} + \mu_{0c}, \Sigma_{\beta_0}) \quad \forall c \in \{1, 2, \dots, 7\} \quad (3)$$

$$\beta_1 \sim N(\gamma_1 + X_i \delta_1 + \mu_1, \Sigma_{\beta_1}) \quad (4)$$

These random effects allow the individual-level response to anticipated labor market earnings, as well as the baseline preference for each major type (β_{0m}) to vary across demographics and, with the data set indicators, across time. Random effects allow the error terms ε_{im} to be correlated across major options, relaxing the independence of irrelevant alternatives assumption in basic conditional logit analysis (McFadden and Train, 2000). Further, the Markov Chain Monte Carlo algorithm produces individual β_{0m} and β_1 coefficient draws for each individual, allowing each individual to have their own response to each anticipated labor market feature.

The identification of the preference parameters is not based on clearly exogenous variation in major-specific earnings, or wage shocks. Rather, identification follows from cross-year

variation in major-specific earnings. By analogy to a linear model, identification is similar to what would be achieved by regressing choice on major-specific earnings with major-specific random effects. If students are more likely to pick a given major in a year where that major’s wages look better than they normally do, relative to other majors, then the model will estimate a positive coefficient on wages. Without exogenous variation in anticipated earnings, it is not clear that the model estimates “preference parameters,” specifically, without further assumptions. However, the estimates are well aligned to answer the question of whether student choice is aligned with labor market demands, which is a policy question of considerable interest. We refer to our estimates as “responses” or “elasticities” on this basis.

Individual coefficient draws, as estimated using the hierarchical Bayes algorithm applied to Equation 2, are used to calculate marginal effects of each labor market feature for each individual. We then compare these marginal effects to see whether major choice responsiveness varies across individuals and changes over time.

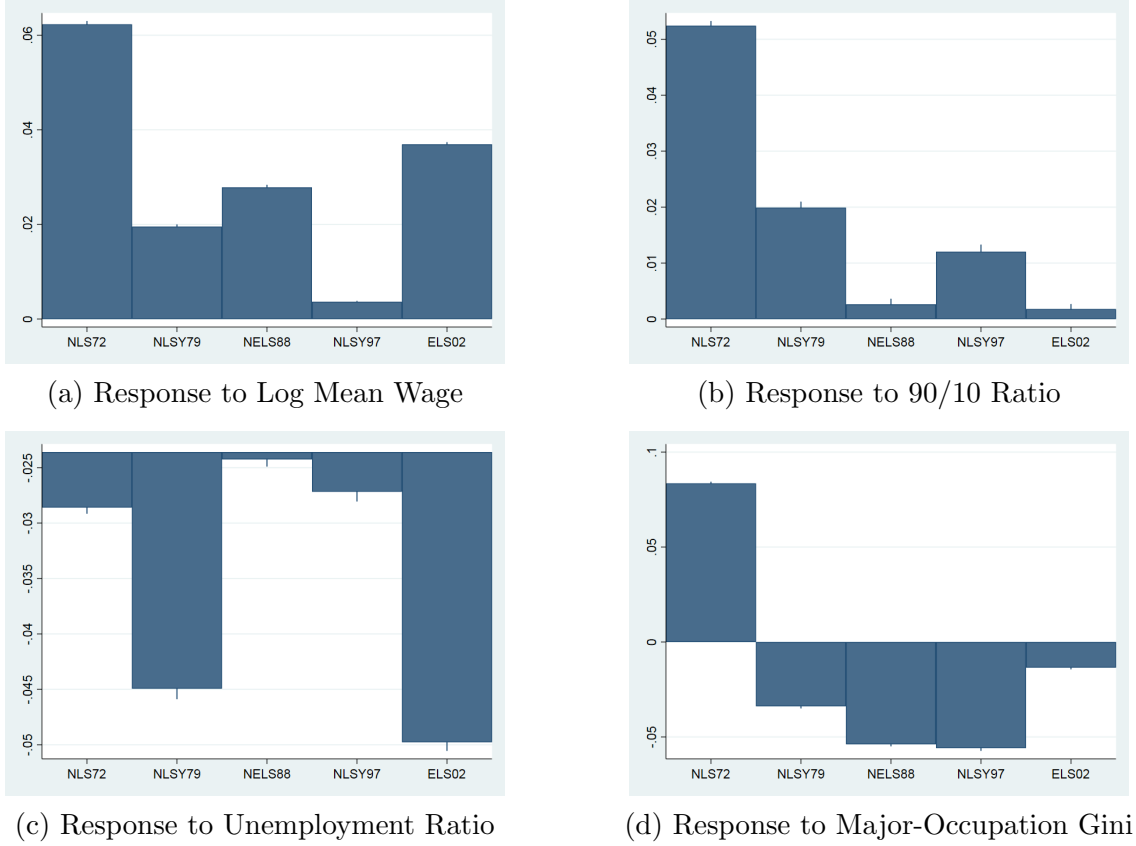
III. RESULTS

III.i. CHANGES IN THE EFFECT OF LABOR MARKET CONDITIONS ON MAJOR CHOICE OVER TIME

Figure A.4 shows changes in the average marginal effect of mean wage, the 90/10 wage ratio, unemployment, and the major-occupation Gini coefficient across the five samples. Sample distributions of each of the coefficients can be found in Appendix A.⁷ Changes across time in the average marginal effect of median wage are substantively the same as for mean wage, and changes in the average marginal effect of the standard deviation of wage and the 90/10 ratio are the same, and so median wage and standard deviation are not

⁷Given that the estimated model is Bayesian, these distributions are presentation of results that best fits the model; frequentist mean comparisons and regressions are used here and in following sections for simplicity of presentation and for the intended audience.

Figure 2: Changes in Average Marginal Effects Across Samples



shown. Changes across time in responsiveness to first-differenced year-to-year wage changes are shown in Appendix [Appendix A](#), and do not follow an obvious time trend. Additionally, results are nearly identical if demographic controls are included. The relationship between demographics and average marginal effects is examined later in Table 2.

In Table [A.4](#) we see meaningful change across time in the relationship between the labor market implications of different majors and their popularity. The difference in average marginal effects from one sample to the next is always statistically significant at the 99% level.

Student response to mean wages does get weaker over time, although the change is not monotonic. The average marginal effect of log mean wages is highest in the earliest sample of

NLS72 at .06229, which translates to an elasticity of about .44.⁸ Later samples have smaller responses, with elasticities of .14 in NLSY79, .19 in NELS88, and only .03 in NLSY97. The effect rebounds somewhat for the ELS02 sample, with an elasticity of about .26. So, relative to the NLS72 sample, the response to mean wages has gotten weaker, but relative to the samples of NELS88 and NLSY97, there is some recovery in the effect. Excluding NLS72, however, the trend is slightly upwards.

Responsiveness to unemployment shows less movement. Students respond most strongly to unemployment in ELS02 and NLSY79, and less strongly in NLS72, NELS88, and NLSY97. While there are differences between years here, there is not any indication of a strong time trend, as the response to unemployment rises and falls from sample to sample. The pattern does not appear to strongly align with periods of US recession, as we might expect if students become more labor-market aware during times of economic downturn (Blom et al., 2017). Similarly, the response to the Gini coefficient seems flat, with the exception of the transition from NLS72 to NLSY79. In NLS72, students were more likely to choose a major that led overwhelmingly to specific majors. Afterwards, choices lean towards majors that lead to a broader array of occupations. But this tendency remains relatively flat over time, getting more negative for NELS88 and NLSY97 but retreating towards 0 for ELS02.

The response to the 90/10 ratio follows a strong time trend, on the other hand. Inequality in the wage distribution actually enters as having a large and positive impact on choice in NLS72. Students in this earlier cohort tended to pick majors with unequal wage distributions, but inequality becomes less important over time. By NELS88 and later, the mean marginal effect of the 90/10 ratio is near 0.

Generally, what we see is students becoming less responsive to certain parts of the labor market (mean wages and inequality in the wage distribution) over time. The starting year does matter, though - if NLS72 is omitted, the trend for response to log mean wage is

⁸Simply, given seven major categories, dividing .06229 by (1/7). Actual elasticity under the implicit assumption that responsiveness is the same across major will be smaller (larger) for more (less) popular majors.

upwards, and the decline in the 90/10 ratio, while present, is less stark. There is less of a discernable pattern for unemployment and the major-occupation Gini coefficient, with obvious year-to-year changes but no clear time trend. Notably, the change in responsiveness to earnings is not due to earlier cohorts having less predictive future earnings over time, and is thus less relevant to the decision. As established in Section II, the predictive power of previous cohorts actually becomes stronger from NLS72 to NLSY79, and then is similarly powerful for NLSY79, NELS88, and NLSY97.

III.ii. DEMOGRAPHICS AND THE RESPONSE TO LABOR MARKET CONDITIONS

In Section III.i we demonstrated that the relationship between the average wages or inequality of wages associated with a major, and the choice of that major, had changed over time. Specifically, the link between those two has become weaker, but the reasons for this change are not clear. In this section, we consider the possibility that demographic shifts in the college graduate population, illustrated in Table 1, explain the change. If the groups that make up an increasing share of college graduates - women, non-whites, and students with lower test scores - are less sensitive to labor market conditions, then we would expect the overall response to drop as well.

Table 2 shows the relationship between the average marginal effect of labor market conditions on major choice and our set of demographic controls. We see some support for the demographic-shift explanation, but not total support. Women, for example, do indeed respond less strongly to mean wages and the 90/10 ratio, but they respond more strongly to unemployment, and we did not see an increase in the impact of unemployment over time.

White students and higher test-score students respond more strongly to mean wages but slightly less to the 90/10 ratio. If the changes were explained by the shrinking proportion of these students, we would not have seen the change in the effect of the 90/10 ratio that we observed.

The mother’s education results are perhaps the most consistent with the changes. Mother’s education of college graduates has increased considerably over time. Higher levels of mother’s education is associated with less response to mean wages and the 90/10 ratio, and inconsistent responses to unemployment and the major-occupation Gini coefficient, matching the overall change.

In Table 3 we use Oaxaca decomposition to analyze the differences in average marginal effects between each sample and the subsequent sample. We determine what part of the change in effect can be attributed to changes in demographics, and what portion can be attributed to changes in the individual-level responses within demographic types.

Keeping with the inconsistent results in Table 2, the Oaxaca decompositions find that the bulk of the change from sample to sample in average marginal effects can be explained by changes of marginal effects within groups, rather than changes in the demographic mix, whether the effect is increasing or decreasing in size. The primacy of changes within groups holds up both for nearly every sample-to-sample change (NLSY97 vs. ELS02 for 90/10 ratio and NELS88 vs. NLSY97 for Gini as the only exceptions) and for changes from the first sample to the last.

From these decompositions we can conclude that changes in responses over time are due to an overarching change in responsiveness, and not to a compositional effect resulting from demographic shifts related to the democratization of college education.

Table 2: Demographic Differences in Average Marginal Effects of Labor Market Conditions

	Marginal Effect of...			
	log(Mean)	90/10 Ratio	Unemployment	Maj-Occ Gini
Female	-0.00949*** (0.00015)	-0.01705*** (0.00026)	-0.02073*** (0.00015)	0.00243*** (0.00026)
White	0.00337*** (0.00018)	-0.00924*** (0.00032)	-0.02061*** (0.00021)	0.01613*** (0.00032)
Family Income				
Quartile 2	0.02691*** (0.00031)	0.03545*** (0.00047)	-0.00285*** (0.00029)	-0.01281*** (0.00047)
Quartile 3	0.00537*** (0.00022)	0.01177*** (0.00044)	0.00210*** (0.00026)	-0.02699*** (0.00044)
Quartile 4	-0.00644*** (0.00023)	0.03867*** (0.00046)	0.00934*** (0.00026)	-0.01559*** (0.00045)
High School Test Score				
Quartile 2	0.02486*** (0.00043)	-0.10308*** (0.00071)	0.05882*** (0.00077)	-0.00411*** (0.00071)
Quartile 3	0.02074*** (0.00040)	-0.07339*** (0.00068)	0.06937*** (0.00075)	-0.02288*** (0.00067)
Quartile 4	0.01349*** (0.00040)	-0.09379*** (0.00067)	0.07935*** (0.00076)	-0.06249*** (0.00066)
Mother's Education				
Quartile 2	-0.01616*** (0.00037)	-0.00164*** (0.00051)	0.00850*** (0.00031)	0.01914*** (0.00050)
Quartile 3	-0.01432*** (0.00038)	-0.02378*** (0.00053)	0.01965*** (0.00032)	0.00514*** (0.00053)
Quartile 4	-0.01159*** (0.00038)	-0.01534*** (0.00054)	-0.00360*** (0.00033)	0.00474*** (0.00054)
Control for Sample	Yes	Yes	Yes	Yes
Observations	14,017	14,017	14,017	98,098
R-squared	0.47307	0.63291	0.51177	0.69441

Table 3: Oaxaca Decomposition of Change in Average Marginal Effect into Demographics and Coefficients

	NLS72 vs. NLSY79	NLSY79 vs. NELS88	NELS88 vs. NLSY97	NLSY97 vs. ELS02	NLS72 vs. ELS02
Response to Log Mean Wage					
Demographics	0.00030 (0.00030)	-0.00021 (0.00047)	0.00025*** (0.00008)	-0.00161*** (0.00051)	0.00090** (0.00039)
Coefficients	0.04433*** (0.00035)	-0.01301*** (0.00021)	0.02524*** (0.00036)	-0.03418*** (0.00021)	0.02370*** (0.00027)
Interaction	0.00126*** (0.00038)	0.00013 (0.00023)	0.00132*** (0.00040)	0.00156*** (0.00044)	0.00077*** (0.00024)
Response to 90/10 Ratio					
Demographics	-0.00501*** (0.00081)	0.00623*** (0.00087)	0.00294*** (0.00090)	0.00381*** (0.00083)	0.00788*** (0.00068)
Coefficients	0.03498*** (0.00049)	0.00992*** (0.00049)	-0.01002*** (0.00046)	0.00147*** (0.00046)	0.03606*** (0.00052)
Interaction	-0.00032 (0.00029)	0.00029 (0.00040)	-0.00007 (0.00015)	-0.00030 (0.00024)	-0.00000 (0.00041)
Response to Unemployment					
Demographics	-0.00104 (0.00073)	0.00231*** (0.00050)	-0.00303*** (0.00060)	0.00353*** (0.00077)	0.00248*** (0.00061)
Coefficients	0.01932*** (0.00029)	-0.02876*** (0.00033)	0.00845*** (0.00024)	0.02005*** (0.00032)	0.02141*** (0.00026)
Interaction	0.00027 (0.00026)	0.00258*** (0.00034)	0.00045*** (0.00014)	-0.00100*** (0.00027)	-0.00076*** (0.00026)
Response to Major-Occupation Gini					
Demographics	0.00323*** (0.00077)	-0.00111 (0.00080)	0.00409*** (0.00093)	-0.00185** (0.00087)	0.00331*** (0.00067)
Coefficients	0.10974*** (0.00046)	0.02018*** (0.00052)	-0.00010 (0.00051)	-0.05187*** (0.00052)	0.07877*** (0.00045)
Interaction	-0.00000 (0.00028)	-0.00013 (0.00041)	-0.00011 (0.00018)	0.00002 (0.00027)	-0.00000 (0.00037)

IV. CONCLUSION

We examine the influence of the labor market potential of college major on the student choice of those majors, and the change of that influence across time. We find that the responsiveness of major choice to the mean and median earnings associated with each major declined overall from the 1970s to the 2010s, although the real decrease in responsiveness was during the 1980s and there has been some rebound since. We also find that the association between major choice and inequality in the wage distribution has gone from positive to unvalued, and there is little change in the response of major choice to unemployment levels or the concentration of majors within occupations as measured by a Gini coefficient. Our work aligns with previous studies showing a positive but relatively weak relationship between labor market potential and major choice in recent data sets (e.g. [Arcidiacono, 2004](#); [Long et al., 2015](#); [Arcidiacono et al., 2011](#); [Boudarbat and Montmarquette, 2007](#); [Stinebrickner and Stinebrickner, 2011](#)). We add to this literature by showing that responsiveness is weaker in these recent cohorts than in earlier ones.

Which factors might explain the low response of undergraduates to earnings associated with majors and an even lower response over time? Demographic shifts in the composition of the undergraduate population could be one explanation. We tracked changes in major choices and earnings over a large change in the demographics of college graduates, as suggested by [Table 1](#). One interesting demographic shift is socioeconomic; the profile of college graduates has moved markedly down the income distribution, to the third family income quartile. We find that these students weigh labor market considerations more heavily than their more socioeconomically advantaged peers. Another major change is in the gender composition of college graduates, towards women, whose choices do not respond as strongly to labor market conditions as men’s choices. Overall, however, we find that the changes in major choice elasticity are better explained by changes of responsiveness within groups than changes in the demographic makeup of college graduates.

These results suggest that factors other than potential earnings have been influential

for undergraduates making choices about college majors, and non-labor market factors may have become more influential over time. Personal taste for major ([Wiswall and Zafar, 2015](#)) may be increasingly dominating the choice process, relative to labor market demand or comparative skill. The college culture and environment has also changed over time, with a number of sociological studies suggesting that college is viewed as a social environment where studying, learning, and planning for the future are secondary to forming relationships and socializing with peers ([Arum and Roksa, 2011](#); [Armstrong and Hamilton, 2013](#)), leading colleges, especially less selective ones, to compete for students on that basis ([Jacob et al., 2018](#)).

An increasing emphasis on non-academic or non-labor factors can be backed up in several strains of literature, but there are some alternate explanations that we have not been able to address. Relatively high-earning majors may have become more skill-intensive and difficult over time, keeping students from responding to financial incentives; students may be entering college more highly specialized and thus less able to respond to labor market shifts; or the persistently high overall college wage premium may have led to satisficing behavior in major choice. One alternative explanation that we can address is that changing behavior may be driven by increasing dynamism in the labor market. If the labor market is more turbulent, choosing a high-earning major could turn out poorly, since the labor market may shift by the time students enter the labor market. On the contrary, we find that the link between prior-cohort and current-cohort earnings within major has remained strong over time. Students should have no reason to believe that majors that seem lucrative now are likely to have low returns later.

When taking these results in context, it is important to note that many of the biggest changes come between NLS72 and NLSY79. Examining the effect distributions in [Appendix A](#) makes it clear that NLS72 stands apart from the other data sets. So, much of the change that we see here is from comparing a somewhat constant modern era against results from many decades ago, rather than a continuous and consistent year-to-year change.

One way to interpret the results is that NLS72 is simply odd and should be disregarded. Taking this approach, the wage response results would, in fact, reverse, albeit with a lower effect size. However, there is no apparent reason in the data to exclude NLS72 other than because it does not fit the narrative established for mean wage responses by other data sets. The predictive power of our wage measure is similar in NLS72 to the other years, and the data collection methodology is similar, although not identical, across NLS data sets.

Moving to a policy standpoint, there is some reason to be concerned with a link between major choice and labor market potential that is considerably weaker today than it was decades ago, since economic development and human capital is one justification for public support of higher education. If students are optimizing less for labor market outcomes at the same time that education is getting more expensive, debt loads could increase, and public support for colleges as drivers of economic production could diminish.

Policy levers exist to “correct” the change in student major choice through policies such as major-specific tuition ([Stange, 2015](#)). It is also possible for institutions to attempt to channel students into particular majors through caps on majors or encouragement. If the policy goal is to maximize the ability of colleges to produce labor-market gains, then the paternalistic application of these types of policies could be warranted to offset the decline in student preference for higher-earning majors, especially if the comparison point for these policies is in the NLS72 era rather than the more recent past for which there is actually not much difference. These approaches, however, are heavy-handed, reducing student freedom and framing higher education explicitly as an economic tool.

This study provides broader perspective on the productive power of higher education. The college wage premium has remained high despite the decline in student optimizing of labor-market returns through major choices. The aggregate college wage premium may actually be understated relative to what it could be if students picked majors in the same way that they did in the past. As an economic engine, colleges could be producing more value than they are now, simply by shifting major choice. Our estimates suggest that the

gap between the labor market value that colleges could produce, and what they do produce, has been growing.

V. ACKNOWLEDGMENTS

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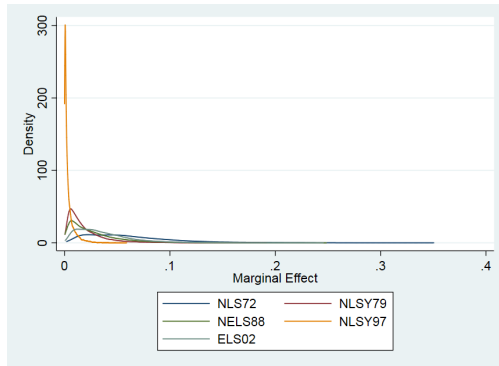
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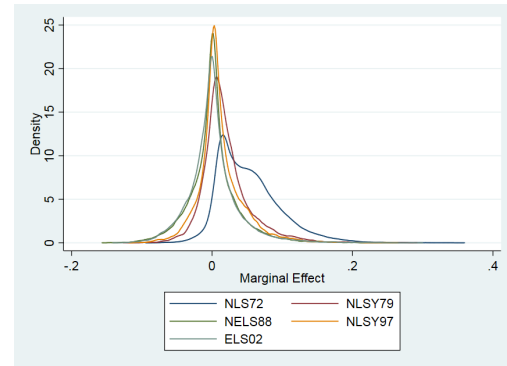
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Appendix A. ADDITIONAL RESULTS

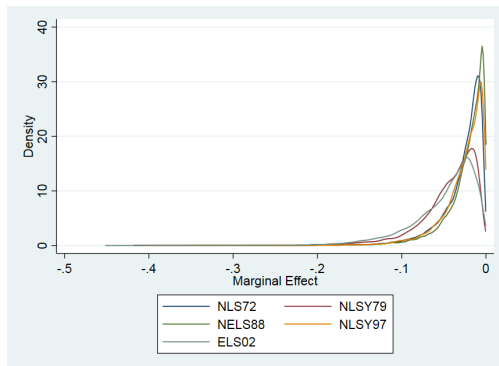
Figure A.3: Distributions of Average Marginal Effects Across Samples



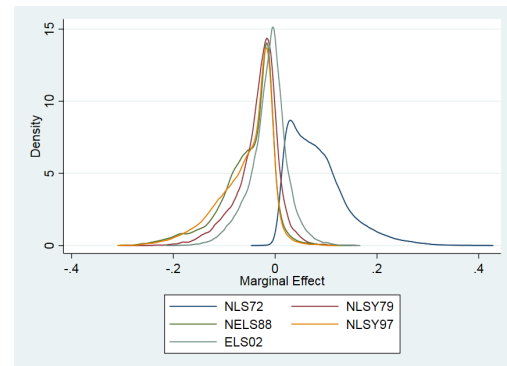
(a) Response to Log Mean Wage



(b) Response to 90/10 Ratio

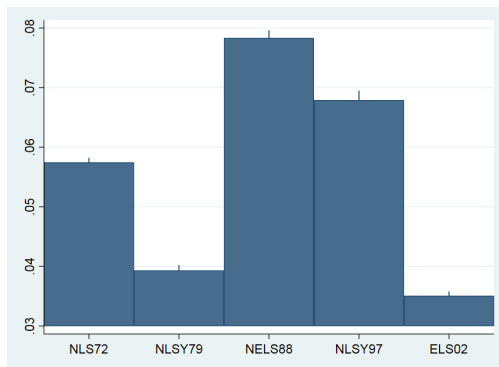


(c) Response to Unemployment Ratio

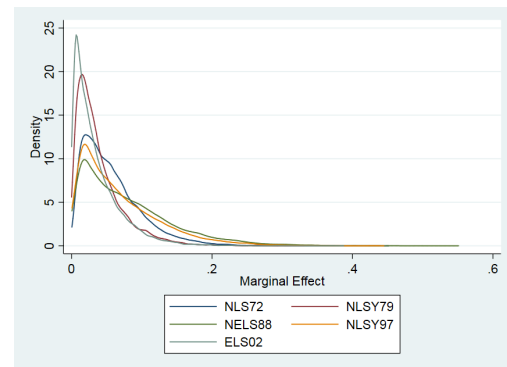


(d) Response to Major-Occupation Gini

Figure A.4: Response to Year-to-Year Log Mean Wage Changes



(a) Mean Marginal Effect Comparisons



(b) Distribution of Marginal Effects