Labor Market Returns to College Major Specificity*

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Abstract

This paper develops a new approach to measuring human capital specificity, in the context of college majors, and estimates its labor market return over a worker's life cycle. After reviewing other measures which have been used to measure specialization, we propose a novel method grounded in human capital theory: a Gini coefficient of earnings premia for a major across occupations. Our measure captures the notion of skill transferability across jobs. Using data from the American Community Survey and the Baccalaureate and Beyond, we find that the most "specific" majors pay off the most, with an early-career earnings premium of 8%, driven by higher hourly wages, and a similar premium later in the career. The most general majors lag behind at every age. Surprisingly, we do not see any evidence that specific fields are riskier than general fields: specific majors do best throughout the wage distribution and do not carry a higher probability of unemployment. Despite their earnings advantage, graduates from specific majors are 20-30% less likely than average majors to become entrepreneurs or hold managerial positions. This finding lends some support to a prominent hypothesis from the literature on managers and entrepreneurs.

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1 Introduction

The existence of large differences in earnings across graduates from different majors is now well established (see Carnevale et al. (2012); Lemieux (2014); Chevalier (2011); Walker and Zhu (2011), among many others), with recent evidence demonstrating that the causal returns to certain majors are also substantial (Kirkebøen et al. (2016), Hastings et al. (2013)). Understanding what drives these differences is important. In order to do so, we need to define and study the characteristics that distinguish college majors.

This paper studies the level of specialization of college majors and estimates the return to specialized college degrees over the life cycle. College major specialization is of interest for two reasons. First, a large body of empirical and theoretical work has studied the role of specialized and general human capital on earnings,[1] but insights from this literature have yet to be applied in a general way to fields of study in higher education. Second, the growing literature on the correspondence between education and occupation has important insights for understanding the return to college majors.[2]

We first summarize the literature on educational specificity and recount the diverse ways in which specificity has been conceived and measured. Previous approaches have emphasized the occupational outcomes of the major, the diversity of the curriculum studied, or categorizations of majors as vocational or academic. These existing measures, while useful and meaningful in their own ways, have no strong basis in economic theory.

To correct this, we propose a novel measure of major specificity grounded in the notion of specific and general human capital from the labor economics tradition (Becker (1962)). In this literature, the specificity of human capital is determined by its transferability – that is, how the value of skills changes when applied in different jobs. Our new measure, a modified Gini coefficient of a major's earnings returns across occupations, captures this notion of transferability of skills across jobs. This measure of specificity produces intuitive results that differ from existing measures, showing that some majors usually considered "specific" actually produce graduates with highly versatile skills (e.g., accounting), while other majors that are often thought of as "broad" actually produce skills that are quite specialized (e.g., economics).

[1]Initiated with the work of Becker (1962), human capital specificity has since been studied as occupation specific (e.g., Kambourov and Manovskii (2009)) task-specific (e.g., Gibbons and Waldman (2004)), firm-specific (e.g., Altonji and Shakotko (1987)), among others.

[2]See Sellami et al. (2016) for a review and discussion of existing approaches to measuring field-of-study mismatch; Liu et al. (2016) introduce a data-driven measure based on relative earnings.

We then apply our new measure to two sets of empirical questions. We first estimate the earnings returns to college major specificity. Using existing measures, there is typically a trade-off between early-career success and later-career success. "Vocational" majors, for example, enjoy a large initial earnings premium of about 15% over "academic" majors, but academic majors overtake vocational majors around age 35 and maintain the advantage through at least age 60.

For our Gini measure, however, there is no such trade-off. Majors which provide specialized skills earn the most both early and late in the career. General majors, which provide transferable skills, lag behind at every age. The earnings effect operates entirely through hourly wages and not through hours worked. Specialized majors do not necessarily provide more access to jobs, but they do provide access to better-paying jobs. For new graduates, the most specific majors earn 8% more annually than the average major (controlling for the demographics of the worker and average ability of the major's graduates). The initial premium fades by the worker's 30s but returns for ages 40-60. Furthermore, we find no evidence that specific fields are "riskier" than general fields. Specialized majors outperform general majors throughout the earnings distribution, and do not have lower probabilities of employment.

Finally, we turn our attention to managers and entrepreneurs. A prominent literature suggests that those with more general human capital will be more likely to enter these types of jobs (e.g. Lazear (2005)). We find some evidence in support of this hypothesis. Despite the advantage of specific majors in average earnings, these majors are associated with about 20-30% lower probabilities of entering entrepreneurship or management occupations, when compared with average majors. However, the most general majors are not more likely than average to lead to management or entrepreneurship. This lends tentative support to the 'jack-of-all-trades' theory of entrepreneurs – although it suggests the effects of specificity are not linear – and also helps validate our measure of major specificity.

Recent literature on the returns to specialization in higher education has typically focused on countries with a well-defined vocational track. Looking across eleven European countries, Hanushek et al. (2017) find that vocational training improves employment outcomes for young people, but that generally-educated individuals are more likely to be employed at older ages. Using Swedish registry data, Golsteyn and Stenberg (2017) find that vocational education is associated with an earnings premium early in the life cycle, but that this premium declines and is overtaken by general education in later years. Brunello and Rocco (2017) find that vocationally-trained workers in the UK have a persistent employment advantage with respect to generally-trained workers, although the magnitude of this advantage declines over the life cycle.

A smaller collection of papers has explored the return to specialization within fields. The most developed strand of this literature studies the return to skills breadth among entrepreneurs. Lazear (2005) introduces the hypothesis that entrepreneurs must be generalists, and finds evidence that both diverse occupational histories and broad educational backgrounds are associated with entrepreneurship. Much of the subsequent literature has focussed on role of diverse work histories (see, among others, Stuetzer et al. (2012), Wagner (2006), Silva (2007)), with little further evidence on the association between education breadth and entrepreneurial activity.[3]

We make three main contributions to the literature. First, we develop a new theory-driven measure of college major specificity, showing that some majors typically thought of as general are actually specific in the skills they teach, and vice versa. We then apply our new measure to make two empirical contributions. In doing so, we show that our Gini measure is distinct from previous attempts to measure specificity and that the conventional wisdom on the returns to specialization is not correct. We provide the first estimates of the return to specific and general college majors, showing that specific majors typically earn the most, and that there is no early-versus-late-career tradeoff between specialized and general skills. Finally, we show the first cross-major evidence in support of Lazear's (2005) jack-of-all-trades theory of entrepreneurship, further validating our approach.

The remainder of the paper proceeds as follows. In Section 2, we review the measures that have been used, explicitly or implicitly, to capture the specialization of higher education degrees. In Section 3, we introduce our new measure, a Gini coefficient of earnings inequality, to proxy for the transferability of majors across occupations. In Section 4, we employ data from a range of sources to calculate and compare various measures of college major specificity, including our own approach. In Section 5, we estimate the earnings returns to specificity, look at some specific job outcomes, and discuss further applications. Section 6 concludes.

[3]In a different context, Ferguson and Hasan (2013) show that specialization pays highly at all ages for Indian civil service workers.

2 Measuring Specialization: Existing Approaches

2.1 Curriculum-Based Measures

Perhaps the most direct method of measuring specialization of a college major is to look at the diversity of courses taken by its graduates. One such approach is to group subjects into categories, and to count the credits earned, or courses taken, in each category (see Silos and Smith (2015) for college credits and Tchuente (2016) for high school courses). Using data from the UK, Dolton and Vignoles (2002) and Malamud (2012) defined breadth of study at A-levels in a similar way. Detailed transcript data can further allow courses to be weighted by their credit hours and grade achieved (as in Rakitan and Artz (2015)).

Course diversity has been used in other ways to measure specialization as well. Lazear (2005) measures the "lopsidedness" of curricula taken by MBA students as the difference between the maximum number of courses a student has taken in any field and the average number of courses taken across all fields. Artz et al. (2014) use a modified version of this approach, taking the difference between credits inside the major and the largest number of credits earned from a department outside the major.

Without access to detailed transcript data, the timing of specialization offers a proxy measure of credit-specificity: early specializers spend a greater share of their education studying a single subject. Malamud (2010) compares early-specializing English university students to late-specializing Scots in this manner. In an early study on this topic, Morris (1973) classifies Ph.D. students as specialized if their bachelor's degree was in the same field as their doctoral studies.

While course-based measures put minimal restrictions on the number of field-of-study categories one can use, some studies have found it practical to aggregate fields quite coarsely. Peri et al. (2015) restrict themselves to STEM versus non-STEM, while Kinsler and Pavan (2015) use science, business, and "other". Malamud (2010), in contrast, includes a range of classifications, with the narrowest including 42 majors.

The data requirements of the curriculum approach are formidable, requiring at a minimum a representative sample of college transcripts for students in each major. This type of classification presents a deeper issue as well: it is not obvious that all college courses, or fields, are equally broad. Suppose the average education major takes 50% of his courses within the education department, while the average mathematics major takes 50% of her courses within the mathematics department. Does that imply that the two degrees are equally specialized? In terms of their course loads, perhaps they are; but if education courses are broader in scope than mathematics courses, then this measure could be quite misleading. It could be equally misleading if some skills are more widely useful than others. A journalism degree is very much focused on learning to write well – and thus might be classified as specific by a curriculum measure – but writing may be a skill which is valued in a wide range of occupations. It is not obvious, then, whether such a major should be thought of as general or specialized.

2.2 Labor Market Orientation of Degree Program

The notion that some fields of study are more closely linked to the labor market than others gives rise to a different family of measures of program specificity. The most widely used is the "vocational" versus "academic" dichotomy (see Hanushek et al. (2017), Brunello and Rocco (2017) and Golsteyn and Stenberg (2017), among many others). This classification of programs is most frequent in countries with established vocational education tracks and is typically based on the educational system's own classification, although recently Kreisman and Stange (2017) apply a similar approach to high school courses in the US.

Even within these two categories, though, some vocational programs are more specialized than others, as Coenen et al. (2015) explore in depth. In determining the breadth of different upper-secondary vocational programs in The Netherlands, the authors use graduates' assessments of whether their education program provides a better match to occupations within their domain, versus occupations outside it. Their measure classifies those programs which, according to graduates' reports, prepare equally well for both types of occupations as broad, while specialized education prepares students better for occupations within their domain. Parey (2016) compares the labor market returns to vocational education versus firm-based apprenticeship training - a type of education which is arguable even more specialized. He finds no earnings differences between the two, but that apprenticeships lead to an early-career employment advantage.

In some cases, a classification of programs as vocational or general in one jurisdiction has been extended to others, as Stevens et al. (2015) do by linking California's community college Taxonomy of Programs to the national Classification of Instructional Programs. Other authors document changes within the vocational track, including a reform in Sweden that extended and expanded the general content of vocational secondary school (Hall (2013)).

Acknowledging that some academic programs have a stronger labor market orientation than others has led some authors to classify college majors as more or less vocational in nature. Saniter and Siedler (2014) classify majors as being labor market oriented if they lead to a particular profession. Bridet and Leighton (2015) employ a similar approach, using a highly restricted set of majors. Such classifications, which in theory may be related to the share of graduates from a certain major that ultimately work in a particular profession (see Section 2.3), are typically heavily reliant on perceived, rather than empirical, relation between majors and occupations.

2.3 Measures Based on Eventual Job Outcome

A third family of measures of specialization, increasingly popular in empirical studies, uses the distribution of graduates across occupations as a measure of specialization. Blom et al. (2015) compute major-specific measures of occupational concentration using a Hirschman-Hirfindahl Index (HHI). By this measure, majors which send most of their graduates to a single or small number of occupations are highly specialized, while those that send graduates evenly across many occupations are general. Using similar intuition, Altonji et al. (2012) calculate the share of graduates from each major who are employed in the three most popular occupations for that major. While an occupation-based measure is simple to calculate, it may be sensitive to the details of the occupational classification being used.

This type of measure is intuitively related to what a student can do with that major after college. Nevertheless, it may not tell much about the breadth of skills held by graduates. Just because the skills of a major are typically applied in only a few occupations does not mean that they are not generally useful in other occupations. Engineering majors, for example, typically become engineers. However, given their strong analytical skills, it is possible that they would also make fine doctors, teachers, and lawyers if they chose to do so. Thus, the skills possessed by graduates of a certain college major may be more or less generally applicable than an occupational measure will capture.

3 A Theory-Driven Measure of Specialization

While these existing measures of major specialization have their merits, none fully captures the notion of specificity as described in the tradition of labor economics. The concept of general and specific human capital originated with Becker (1962), who distinguished between human capital that is useful in any firm (general) and human capital that is useful in only one firm (specific). Examples of general human capital might be interpersonal skills, critical thinking, and problem solving, while specific skills might include the particular software used by the worker's firm or knowledge of local systems and personnel.

Specificity need not be tied to the firm, however. Economists following Becker's lead have explored the ideas of industry-specific human capital (Neal (1995)), occupation-specific human capital (Kambourov and Manovskii (2009)), and task-specific human capital (Gibbons and Waldman (2004)). In all of these formulations, the difference between general and specific human capital is its transferability. If human capital is general, it is useful across occupations, industries, or tasks. If human capital is specific, it is only useful within a given occupation, industry, or task.

In order to properly measure the specificity of human capital, we must measure how a certain set of skills is *valued* in different jobs. A major may only teach a narrow set of skills, but if those skills are highly valued everywhere, then these skills are transferable. This major should be counted as general rather than specific. On the other hand, if a major's skills are only valued highly in one type of job, then the major is specific.

The existing measures of specialization lack two key things. First, they do not use earnings information in defining specificity, which is essential to measure the value of skills. Job outcomes and course content are inadequate without information on the value of skills. Second, they lack the notion of a counterfactual. If the worker were not in this job, what would she be earning elsewhere? While the latter is unobservable, our approach attempts to include these two elements.

We propose a new measure of college major specificity based on the transferability of graduates' skills, incorporating information on earnings for a major across occupations. We focus on occupations as the relevant unit of analysis, because occupations can be thought of as bundles of tasks with particular relevance in the labor market. Furthermore, previous research has found occupation- and task-specific human capital to be powerful concepts (e.g., Poletaev and Robinson (2008)). A general major, then, is one whose graduates perform equally well across occupations – that is, their skills transfer in a similar manner to any occupation. A specific major would be one whose graduates perform well in some occupations and poorly in others, so that their skills are not as transferable.

Consider the three hypothetical majors presented in Figure 1. Imagine that there are eleven occupations (as we will use in calculating our measure) and that we plot the earnings premium of each major in each occupation, arranged from lowest to highest. Each point on the figure gives the major's log earnings premium relative to the average major in that occupation. If the point is at 0, the major has an average return in that occupation.

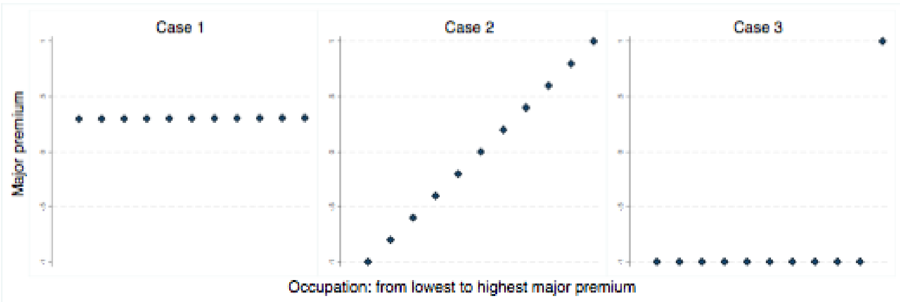


Figure 1: **Distribution of earnings premia across occupations: hypothetical cases**

The graph of hypothetical Case 1 (Figure 1, leftmost panel) shows a flat line, meaning that this major's graduates receive a similar premium across occupations. In this case, the major earns a premium about 30% above average in every occupation. We call this a general major. This can occur if the major's graduates are near the bottom of every occupation, near the middle of every occupation, or near the top of every occupation. A perfectly flat line would mean that the graduates earn exactly the same return in every occupation, relative to the average major in that occupation. The flatter the line, the more general the major is.

On the other hand, consider Cases 2 and 3 in the same figure, which show two types of specific majors. Case 2's graduates are exceptional at one occupation, poor at another, and are "in-between" at everything else. Here, no matter what occupation the graduate is in and what occupation she switches to, the degree to which her skills are rewarded will change. In no two occupations are her skills equally valued.

In Case 3, the major's graduates are exceptional in one occupation and poor in every other occupation. This is clearly also a more specific major than Case 1, because if a graduate moved from the exceptional occupation to any other occupation, her skills would not transfer much at all. Cases 2 and 3 are therefore two examples of specific majors. In each case, graduates can be found at the top and at the bottom of an occupation.

These hypothetical graphs show us that to properly measure major specificity, what we want is a measure of the inequality of earnings premia for a major across occupations. Case 1 shows an equal distribution of earnings premia across occupations. If this major were a country, and each occupation a person, it would show the lowest possible level of inequality. Cases 2 and 3 would be rated as more unequal. Thus, we look for a measure of inequality to capture our notion of major specificity.[4]

The large literature on measuring inequality provides guidance in selecting a measure suited to this task.[5] The Gini coefficient is a natural choice. It has the advantage of being a familiar and widely used measure, but it also has other desirable characteristics. It maintains properties of symmetry (in our case, relative excellence in one occupation is equivalent to relative excellence in another) and population size independence (small and large majors can be accommodated). With a small modification we discuss below, it is also level-invariant, meaning two majors with identical graph "shapes" but at different earnings levels will be treated the same.

We proceed as follows. First, we estimate the earnings premium for each major in each occupation using occupation-level regressions. Then, using those estimated premia, we compute a Gini coefficient for each major.

To estimate the earnings premia, we use the American Community Survey from 2009 to 2015, restricting to those aged 25-35. We do this because we wish to focus on skills acquired during college, rather than those learned on-the-job, through further training, or through job-to-job transitions. Our estimating equation controls for those individual and major-specific factors for which we have information, and also includes major fixed effects. Observations within the regressions are weighted by the inverse size of each major-occupation cell to give equal total weight to each cell. We interpret the coefficients on these fixed effects as the major's premium (net of other covariates) in that occupation. Separately for each

[4] Of course, the occupations that graduates go into are not random. The ideal way to measure skill transferability would be to randomly assign students to occupations. Absent this possibility, one could look at the change in wages for occupation switchers. However, switchers are also a highly selected group. Even if one found an exogenous reason for switching, the destination occupations would still be endogenous, and one would need switchers from every occupation to every other occupation to properly measure transferability. Our approach is more feasible.

[5] See Cowell (2000)'s chapter in the Handbook of Income Distribution for an excellent introductions to this body of work.

occupation, we regress:

$$ln(earn)_{im} = \beta_0 + \Gamma_1 X_i + \Gamma_2 SAT_m + year_i + m_i + \epsilon_{im} \quad (1)$$

where the X_i includes gender, race/ethnicity, and a quadratic in potential experience.[6] The SAT_m variables are the average SAT math and verbal scores for the major; as we do not have individual-level SAT scores in the ACS data, these are taken from the 1993/2003 Baccalaureate and Beyond restricted-use data set. We also include year fixed effects. The dependent variable is log wage and salary income for the year, in constant dollars.[7]

The major fixed effects m_i give the earnings return, net of demographics and average SAT scores, for each major in each occupation. We use 51 majors and 11 occupations, so we run 11 of these regressions and estimate 51 major premia for each one. We then de-mean these premia by subtracting the average premium over all majors within that occupation, so that for each occupation the average premium is zero. Using these modified earnings premia, we compute a Gini coefficient for each major, as follows:

$$G_m = \frac{1}{2n^2} \sum_{j=1}^{n} \sum_{k=1}^{n} |m_j - m_k| \quad (2)$$

where n is the number of occupations (11 in our case) and m_j and m_k are the de-meaned premia for major m in occupations j and k. Note that this "absolute" Gini measure is slightly different from the "relative Gini" most commonly used to compute a nation's inequality. The absolute Gini deals better with negative values, and makes the measure level-invariant.[8]

Now let us compare the estimated earnings premia for actual majors in our dataset to the hypothetical cases in Figure 1. In Figure 2, we graph the estimated premia for six majors: psychology and other social sciences on the left, finance and computer programming in the middle, and our two education majors on the right.[9]

[6]Potential experience is measured as survey year minus college graduation year, implied from the date of birth.

[7]Including region or division fixed effects has no effect on the results.

[8]The more common "relative" Gini would divide by the average m for the major across occupations, which is a problem in our case because that mean is often very close to zero, and sometimes negative. The relative Gini is also scale-invariant rather than level-invariant, meaning that a proportional increase in all data points would keep the measure constant. The absolute Gini's property of level-invariance is more appropriate for our context.

[9]Secondary education is here grouped with specialized education (e.g., “science education”), while primary and general education majors are grouped together.

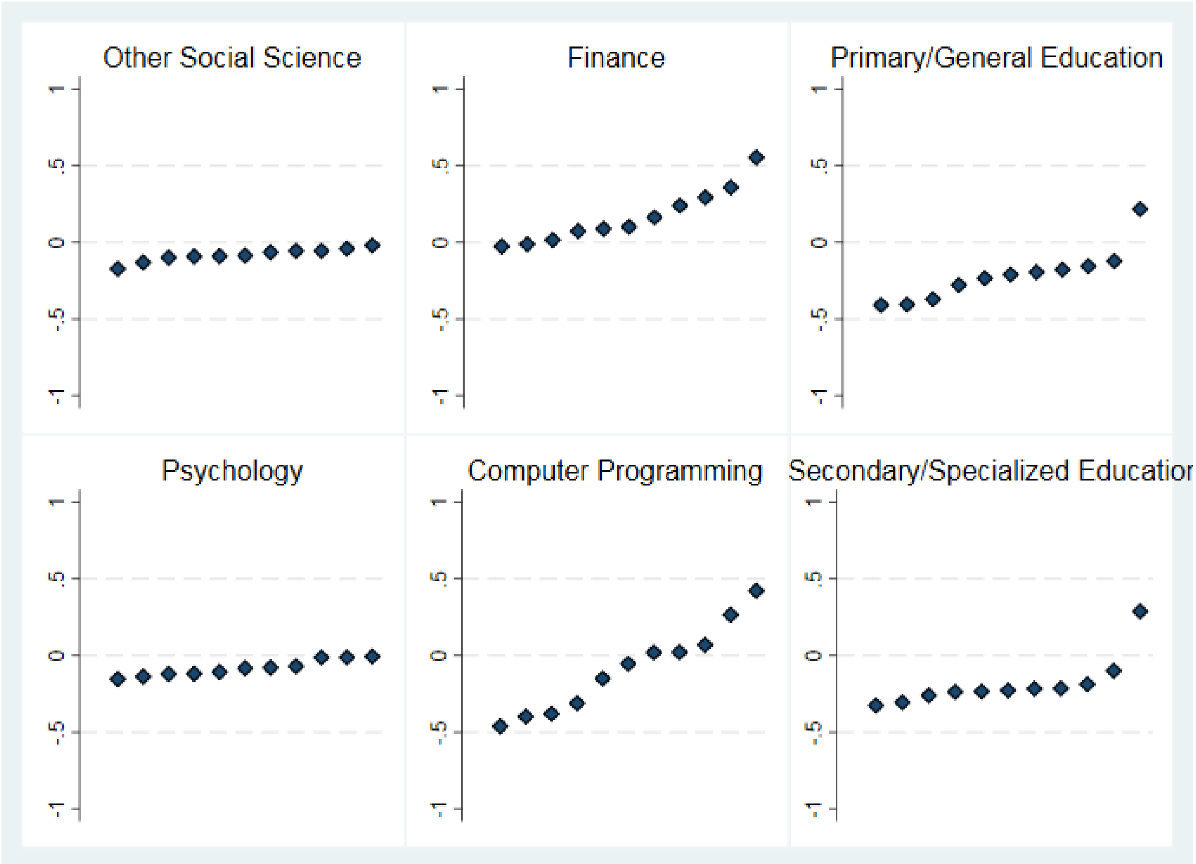


Figure 2: **Distribution of earnings premia across occupations: examples of type cases**

Psychology and other social sciences look much like Case 1 from Figure 1. The lines are relatively flat, showing that graduates of these majors earn similar premia in each occupation. Both majors earn an average or just below average premium in every occupation. Based on Figure 1, we argued that majors like this should be considered very general, as their skills are highly transferable across occupations. As it turns out, psychology and other social sciences are two of the three most general majors as rated by our Gini coefficient.

Finance and computer programming look similar to hypothetical Case 2. Computer programming, for instance, earns an exceptional return in a couple of occupations and a well below-average return in several others, with the rest in between. These majors' skills appear to not be so transferable, as their value depends heavily on what occupation the graduate is working in.

The education majors on the right look similar to Case 3. The premium in most occupations is below average, but is substantially higher in one occupation, which in this case is the education occupation.

The four majors on the right of Figure 2 are all rated as specific by our Gini measure. In fact, computer programming is the most specific major of all, with finance fourth, primary education sixth, and secondary education thirteenth. Visual inspection of the data tells us that all of the most general majors show "flat" lines, while the most specific majors all resemble Cases 2 or 3, or some combination of the two.[10]

The earnings premia we estimate are net of demographics and major-average SAT scores. Of course, there are relevant variables that we do not observe, which may differ across majors. Our major fixed effects pick up the effect of these variables – to the degree they are not picked up by SAT scores and demographics – as well. Given that we care about the variation in premia *within* a major *across* occupations, our approach is valid as long as these unobserved factors are valued similarly across occupations. We are encouraged by the fact that our ranking of majors (and results as we report in Section 5) is similar if we vary the control variables included in Equation 1.[11]

A small number of papers conceptualize specificity in a similar way to our approach. Although specificity is not the focus of their paper, Borghans and Golsteyn (2007) directly

[10] A list of the most specific and most general majors is found in Table 3.

[11] For example, we obtain essentially the same results from an approach which regresses log earnings on SAT scores and major dummies, with no demographic controls. The same is true if we include the demographic controls without the SAT scores. In each case, the correlation between that Gini measure and our preferred Gini is 0.97 or higher, and the same majors top the lists of most specific and general majors.

estimate the transferability of skills between fields of study and fields of work. The authors rely on individuals who have "switched" fields, either within education or on the labor market. In the latter case, they rely on self-reported mismatch between education and occupation. Hartog and Vijverberg (2007), using occupations rather than education to define skill sets, estimate the mean and variance of wages in occupation cells defined by the reasoning, language, and math requirements given in the Dictionary of Occupation Titles (DOT). They find that combinations of language and math skills increase wage risk for college-educated men and women, when compared to having a high level of skill in either one.

Kinsler and Pavan (2015) and Coenen et al. (2015) address the issue of specificity explicitly, and therefore come closest to what we do here. Kinsler and Pavan (2015) estimate major specificity by comparing wages of students in related and unrelated occupations. Coenen et al. (2015) observe that an individual's productivity depends on the alignment of their skills with those required in their occupation. Both papers rely on self-reports by respondents on the link between their education and their work. Our goal here is to derive a measure of specialization that exploits the differential earnings of graduates from one major across a wide range of occupations, without relying on subjective assessments of the link between fields of study and fields of work.

4 Empirical Comparison of Measures

4.1 Data

We combine information from two data sets to calculate our new Gini measure and three measures from the families described in Sections 2. For measures requiring data on major, occupation, and earnings, we use the American Community Survey (ACS) from 2009 to 2015. To calculate the concentration of credits within the college curriculum, we use transcript data from the restricted version of the 1993/2003 Baccalaureate and Beyond (BB) dataset. We also use this dataset to generate statistics on the pre-college ability level of student entering different majors, measured as the major-level average and standard deviation of SAT scores.

For those measures which rely on labor market experiences, we use data from individuals aged 25 to 35. Given that we are interested in proxying for the skills acquired in college, it is natural to focus on in the early part of their working lives. As a baseline, we use a set of 51 majors defined by the Baccalaureate and Beyond public-use data set (see Table A.1 in the Appendix). This is so we can compare our measures with other major-level characteristics from that data set, including average SAT scores.

4.2 Definition of Measures

4.2.1 Occupation-based measure

We use an occupational Hirschman-Herfindahl Index (HHI), as used by Blom et al. (2015), to measure the specificity of majors according to occupation. The HHI is calculated as follows:

$$HHI_m = \sum_{o=1}^{N} s_{mo}^2 \tag{3}$$

where m denotes the major, o denotes each occupation, and s_{mo} denotes the share of graduates from major m that work in occupation o. This measure varies theoretically between 0 and 1, with higher values representing more specific majors – those whose graduates are concentrated in a small number of occupations. A value of 1 would represent a major for which all graduates enter a single occupation. We put the measure in standard deviations for ease of interpretation. To explore the robustness of this measure, we have also calculated a "Top 5" measure, defined as the share of students from each major going to the five most common occupations for that major, similar to that used in Altonji et al. (2012). This is highly correlated with the HHI measure ($\rho > 0.9$) and behaves similarly in our applications.

4.2.2 Curriculum-based measure

We measure course specialization as the concentration of courses taken by graduates of that major, computing a Hirschman-Herfindahl Index of courses, as described above. In this case, the HHI is calculated as follows:

$$HHI_m = \sum_{f=1}^{N} s_{mf}^2 \tag{4}$$

where m denotes the major, f denotes a coarse grouping of fields of study,[12] and s_{mc} denotes the average share of undergraduate credits (not courses) earned in field f by students graduating from major m. This measure varies theoretically between 0 and 1 with higher values representing more specific majors – those whose graduates took most of their courses in a one or a few fields. A value of 1 would represent a major in which graduates took all their classes within one field. We put the measure in standard deviations for ease of interpretation.

In addition to the course HHI, we have experimented with two other measures. First, we have constructed an HHI based on all courses taken by a student, rather than the aggregated categories we use in our main measure. We first assign each and every course to a certain major and then calculate the HHI based on those classifications. Second, we have measured the share of total credits earned by a graduate that are from that graduate's own major. Surprisingly, these three measures are not highly correlated. The correlations between them are positive but range only from about 0.1 to 0.3. Thus, unlike occupation-based measures, curriculum-based measures are highly dependent on which measure one chooses.

4.2.3 Labor market orientation

Although the United States does not have the pronounced vocational versus academic distinction present in many European countries, it is interesting to compare how other measures of specialization align with such a binary ordering. The National Center for Education Statistics (NCES) provides a classification of majors into academic (or liberal arts) and career (or career technical) education.[13] We use this classification to code college majors as vocational or academic. We interpret those majors classified as career technical education as vocational, i.e. specialized, while academic majors are interpreted as general. Table 1 presents the broad categories of majors according to this taxonomy.

4.3 Comparing the Measures

We compare our Gini measure to the others in two ways: by exploring the correlation between the measures, and by comparing the majors rated as the most specific and general

[12]For this measure we use relatively broad field categories: math, social science, business, foreign language, science and engineering, humanities, education, computer science, personal development, and other.

[13]This taxonomy can be found: https://nces.ed.gov/surveys/ctes/tables/postsec_tax.asp.

Table 1: **Vocational/Academic Categories**

Liberal Arts Education (Academic, General)	**Career Technical Education (Vocational, Specialized)**
Fine/performing arts	Agriculture and natural resources
Humanities	Business management
Interdisciplinary studies	Business support
Letters/English	Communications and design
Mathematics	Computer and information sciences
Science	Education
Social and behavioral sciences	Engineering, architecture and science technologies
	Health sciences
	Marketing
	Consumer services
	Protective services
	Public, legal, and social services
	Manufacturing, construction, repair, and transportation

Source: top level categories abridged from NCES Postsecondary Taxonomy.

majors by each measure.[14]

Table 2 presents correlations between the measures, as well as correlations between each measure and three major-level test ability/skill measures: average SAT Math scores, average SAT verbal scores, and the standard deviation of SAT scores in the major.[15] All four specificity measures are positively correlated, though none of the correlations are incredibly strong, and it is clear that our measure is distinct from the others. The Gini is most correlated with the occupational HHI measure ($\rho = 0.43$). This means that majors with more easily transferable skills (low Gini) are more highly dispersed across occupations (low occupation HHI), and vice versa. The Gini is also positively correlated with the vocational indicator.

Interestingly, the Gini measure is only weakly correlated with the curriculum HHI measure ($\rho = 0.08$). Because Gini measures the transferability of skills, one might have thought that it would be closely related to a measure that looks at course content (the skill inputs) directly. The weak relationship shows that just because a major requires only a narrow set of classes does not mean the skills taught by those classes are not widely applicable.

The other notable thing from Table 2 is the correlation between each measure and the average SAT scores in the major. Ideally, a specificity measure should be orthogonal to the ability of graduates from the major, as there is nothing about a major being "high-skill"

[14] For a full list of the majors' ranks on each measure, see Table A.1.
[15] These correlations are given with one observation per major – that is, with all majors weighted equally.

or "low-skill" that should make it general or specific. Here, Gini is not strongly correlated with SAT scores, with a slight positive correlation with SAT math scores ($\rho = 0.16$) and no correlation with SAT verbal scores. Despite being positively correlated with the Gini, both the vocational and occupation HHI measures show a negative correlation with both SAT variables. We view the weak correlations for Gini as a benefit of our approach, and this shows that our measure is picking up distinct information from that of the occupation measure.

Table 2: **Correlations Between Major Specificity Measures**

Major measure:	Gini	Occ HHI	Curr HHI	Vocational	Avg SAT M	Avg SAT V	SAT St. Dev.
Gini	1.000						
Occ HHI	0.428	1.000					
Curr HHI	0.082	0.217	1.0000				
Vocational	0.323	0.336	0.122	1.000			
SAT M	0.158	-0.146	0.197	-0.189	1.000		
SAT V	-0.020	-0.261	0.185	-0.474	0.719	1.000	
SAT St Dev	-0.079	-0.220	-0.006	-0.193	0.021	0.248	1.000

We next inspect the most specific and most general majors, as ranked by our three continuous measures, in order to get a feel for where the correlations are coming from. Table 3 shows the top and bottom ten majors by each measure. The majors in italics are those that appear on the same list for all three measures. These are the majors that all three measures agree are very specific or very general. The majors in bold are those that are one of the ten most specific majors by one measure and one of the ten most general majors for another measure.

There is some broad agreement. Nursing and civil engineering are among the most specific majors by all three measures. However, there is also much disagreement. Economics, for example, has one of the most general curricula but produces some of the most specialized, least transferable skills according to the Gini measure. Education majors follow a similar pattern, with a broad curriculum and specific skills.[16]

The Gini measure also shows that traditional categorizations of majors mask variation in specialization. On average, STEM (science, technology, engineering, and mathematics) majors are somewhat specific (0.36 standard deviations above the mean major), according

[16] Another notable difference not shown in the table is the accounting major, which ranks highly on the occupational HHI and is typically considered to be highly specialized. The Gini measure ranks accounting the 14th most general major.

to the Gini measure. However, STEM majors are scattered throughout the distribution of specificity: five are in the top ten majors, but engineering technology, computer science, and other engineering are in the bottom ten (and mathematics is just outside the bottom ten). The average specificity rank of a STEM major is 21st out of 51 majors. One can thus not say that STEM majors are all specific or general. Arts, humanities, and social science (AHSS) majors are quite general (0.72 standard deviations below the mean major), although commercial art and design ranks in the top 15 most specific majors.

Table 3: **Majors in Top and Bottom Ten of Specificity**

Specificity measure:	Occupational HHI	Curriculum HHI	Gini
Most specific	*Nursing*	**Film and Other Arts**	**Computer Programming**
	Primary/General Education	Chemical Engineering	*Nursing*
	Secondary Education	Architecture	Medical Technology
	Accounting	*Civil Engineering*	Finance
	Commercial Art and Design	*Nursing*	*Civil Engineering*
	Civil Engineering	Commercial Art and Design	Primary/General Education
	Medical Tech	Mechanical Engineering	Chemistry
	Architecture	Protective Services	Physics
	Social Work/Human Resources	Precision Production/Industrial Arts	**Economics**
	Computer Programming	Social Work/Human Resources	Mechanical Engineering
Most general	Environmental Studies	Mathematics	Other Social Sciences
	Communications	**Secondary Education**	Music/Speech/Drama
	Other Social Sciences	Computer Science	Psychology
	Misc. Business/Med Support	Fitness and Nutrition	Philsophy and Religion
	Public Health	**Misc. Business/Med Support**	Environmental Studies
	General Science	**Computer Programming**	Area Studies
	Film and Other Arts	General Science	Engineering Tech
	Agriculture	Engineering Tech	Other Engineering
	Business	**Economics**	Computer Science
	Area Studies	Business	History

In the "Most specific" section, majors are listed from most specific to less specific. In the "Most general" section, majors are listed from least specific to more specific. That is, for occupation HHI, nursing is the most specific and environmental studies is the most general. Majors in italics appear on the same list for all three measures. Majors in bold appear on most specific and most general lists for different measures.

5 Estimating the Returns to Specialized Education

5.1 Data

We use the American Community Survey (ACS) from 2009 to 2015 to estimate the returns to college major specificity. Since 2009, the ACS has asked for the respondent's college major, allowing us to study earnings patterns by field of study. We retain all respondents aged 23 to 60 with a bachelor's degree or higher and map their college majors (given in about 100 different codes) into the 51 Baccalaureate and Beyond major categories. We then merge in the four major-level measures of specificity computed in Section 4, as well as major-average SAT scores from the Baccalaureate and Beyond 93:03 data.

In addition to college major for each respondent, we have gender, race/ethnicity (black, Hispanic, Asian/Pacific Islander, and other), and level of highest degree (bachelor's, master's, professional, or doctoral degree). We infer the year of college graduation based on the respondent's birth date and calculate potential experience as the current year minus the inferred graduation year.

Our first outcome of interest is annual wage and salary income, which we top-code at \$500,000. We then explore how major specificity is related to hours, hourly wages, employment, and the probability of holding managerial roles or being an entrepreneur. Our estimating equations also include the major-level SAT measures (average SAT Math and Verbal scores and the standard deviation of SAT scores) as control variables. These test scores proxy for the skill level of the major, while the standard deviation of SAT measures the variance in ability of students who enter the major. The standard deviation is included to ensure that the specificity of a major's *outcomes* is not merely picking up that a broad or narrow set of students enter that field. By including these measures, we can be confident that our estimated return to specificity is not driven by some majors attracting higher ability students – or a wider array of students – than others.

5.2 Estimation

We estimate regressions of the form:

$$y_i = \beta_0 + \beta_1 \text{exp} + \beta_2 \text{exp}^2 + \beta_3 \text{spec}_i + \beta_4 \text{spec}_i * \text{exp}^2 + \Gamma_1 X_i + \Gamma_2 M_i + \text{year}_i \tag{5}$$

where *exp* is potential experience, $spec_i$ is a measure of major specificity, X_i is a set of personal characteristics including gender and race, and M_i is a set of major characteristics apart from specificity. We also include year fixed effects to control for changing economic conditions, which is particularly important over this time period that includes much of the

Great Recession.[17]

In our data, some majors have far more observations than others.[18] This means that unweighted regressions would primarily measure the return to specificity among the large majors, while small majors would contribute little to the results. Because we want to measure the return across all majors, we weight our regressions by the inverse of the major size, which gives equal weight to all of our majors.

5.3 Earnings Returns: Existing Measures

We first estimate the earnings returns to college major specificity using the three existing measures of specialization: the occupational HHI, the curriculum HHI, and the "vocational" indicator. For the first two measures, we believe we are the first to empirically estimate the returns to specificity, and we are the first to apply the vocational measure in estimating the return to four-year degrees in the United States.[19]

We start by estimating Equation 5 using each specificity measure separately, first alone, then interacted with potential experience (note that the vocational measure is binary, while the other measures are in standard deviations). Results are presented in Table 4. The occupation HHI and vocational measures show a similar pattern: a strong initial earnings return (about 7% for occupation HHI and 18% for vocational) which declines with experience. The curriculum HHI, however, shows a slight negative return to specific majors.

[17]Our results come from a combination of the Great Recession and the post-recession period. We have run all of our results for the two periods separately (e.g., 2009 to 2012 and 2013 to 2015), and results are similar for both sub-periods.

[18]For instance, primary education and business each have over 250,000 observations, while majors like public health and area studies have fewer than 15,000. Computer programming is by far the smallest major at about 2,000 observations. The average number of observations for a major is about 59,000.

[19]For all results, we take only the first reported major if the respondent reports a double major. Results are nearly identical when excluding double majors.

Table 4: **Earnings Return to Specificity**

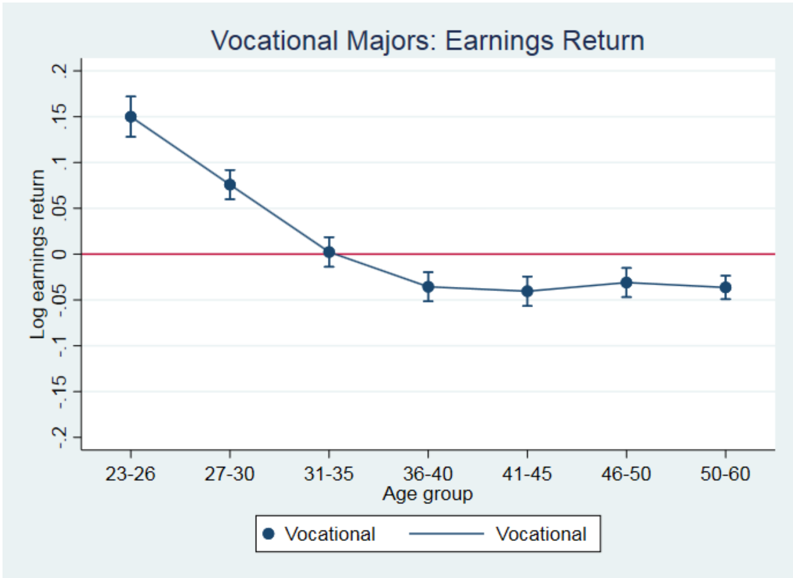
	Dependent variable: log annual earnings							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Occupation HHI	0.015***	0.073***						
	(0.001)	(0.002)						
Occ HHI*potexp		-0.007***						
		(0.000)						
Occ HHI*potexp^2		0.000***						
		(0.000)						
Curriculum HHI			-0.004***	-0.002				
			(0.001)	(0.003)				
Curr HHI*potexp				-0.002***				
				(0.000)				
Curr HHI*potexp^2				0.000***				
				(0.000)				
Vocational					-0.007***	0.180***		
					(0.002)	(0.006)		
Vocational*potexp						-0.019***		
						(0.001)		
Vocational*potexp^2						0.000***		
						(0.000)		
Gini							0.028***	0.056***
							(0.002)	(0.007)
Gini*potexp								-0.004***
								(0.001)
Gini*potexp^2								0.000***
								(0.000)
Constant	32.195***	32.361***	31.276***	31.048***	31.280***	31.624***	29.417***	29.379***
	(0.940)	(0.940)	(0.934)	(0.935)	(0.929)	(0.929)	(0.927)	(0.926)
Observations	2,598,334							
R-squared	0.134	0.134	0.134	0.134	0.134	0.135	0.134	0.135

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All regressions also include gender, race/ethnicity, a quadratic in potential experience, year dummies, a cubic in average SAT Math and Verbal scores in the major, and the standard deviation of SAT scores in the major. The dependent variable is log annual wage and salary earnings. The Gini, occupation HHI, and curriculum HHI are in standard deviations, while vocational is a binary variable. Data: ACS 2009-2015, college graduates aged 23 to 60.

There is no particular reason why we would expect the returns to specificity to be linear. In Figures 3-5, we look at the returns for the most specific and most general majors by each of the three existing measures at different ages. Each figure plots the coefficient of interest from a series of regressions of log earnings, by age group. Figure 3 graphs the estimated return to vocational majors, relative to academic majors. For the continuous measures, Figures 4 and 5 show the estimated return to a dummy variable for being among the ten most specific and ten most general majors, relative to the majors in the middle. Results are similar for narrower or broader definitions of specific majors (such as top/bottom five or top/bottom fifteen majors).

The vocational measure (Figure 3) shows a strong initial earnings return to vocational majors of about 15%, which declines with age. By age 31-35, the return is gone, and for ages 36-60, academic majors outperform vocational majors. The story told by the vocational measure is that specific majors are best (by far) early in the life cycle, while general majors pay off more starting in a worker's 30s.

Figure 3: **Earnings Return: Vocational**



Our "vocational" measure has a very different meaning here than in papers studying European educational systems, for two reasons. First, we use college graduates only, defining vocational and general based on the college major. Second, the United States does not have a tracking or apprenticeship system as in many European countries. In our case, vocational implies that a major is closely connected to particular jobs in the labor market.

Despite these differences, our results are consistent with a recent literature estimating the returns to vocational and general education. Hanushek et al. (2017) estimate the return to vocational education in a sample of eleven European countries with sizable vocational education systems. They find that individuals with vocational education have higher employment rates early in life, but that general education becomes more valuable as the individual ages. They point to this as evidence that general education provides a less clear transition from school to work, but it provides adaptability that pays off over time. Using Swedish data on individuals in secondary school programs, Golsteyn and Stenberg (2017) find results consistent with those in Hanushek et al. (2017). Like these papers, we find that vocational majors have a large positive return early in the career, but that academic majors pay off the most starting in a worker's 30s.

Next we move to the two continuous measures, the occupation HHI (Figure 4) and the curriculum HHI (Figure 5). For these two measures, there is never a strong return to the most specific or the most general majors. Both suggest that specific majors start ahead of general majors and then are passed relatively early in the career path, but in both cases, the majors "in the middle" are actually the highest-earning at most ages. These two measures tell similar stories to each other, but the conclusion is somewhat different from the vocational measure. For the occupation HHI, the most specific majors are the best initially, but this small advantage does not last long.

Figure 4: **Earnings: Occupation HHI**

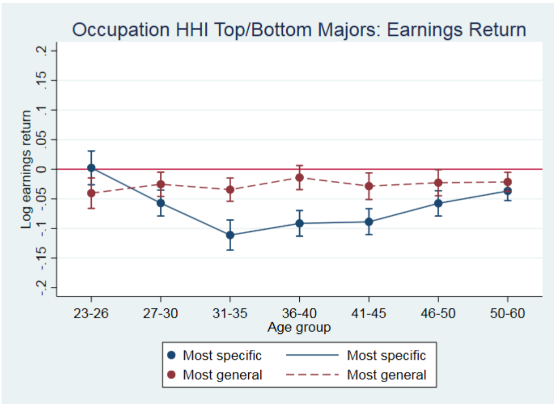
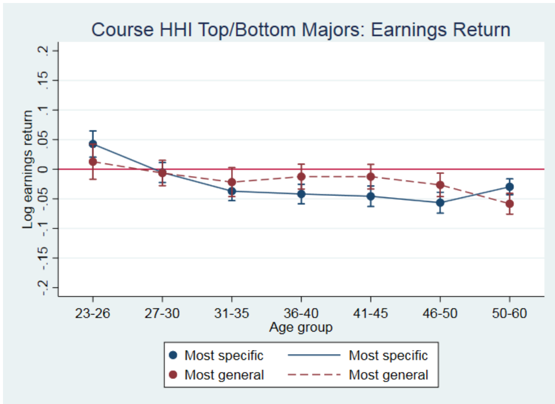


Figure 5: **Earnings: Curriculum HHI**



The three existing measures do not tell a fully consistent story. All three tell us that the best time to be from a specific major is early in the career, but they differ on how good that outcome is. For vocational majors, the early-career advantage of specific majors is large. All three also hint that general majors outperform specific majors later in the life cycle.[20]

5.4 Earnings Returns: Gini Measure

We now estimate the return to college major specificity using our new measure, the Gini coefficient. The last two columns of Table 4 show that more specific majors have an initial earnings return of about 6% per standard deviation, which fades slowly with age. This is the same pattern seen in the vocational and occupation HHI measures, although the coefficients suggest that the positive return fades more slowly for our measure.

[20] To explore the role of graduate degrees in this analysis, we have estimated the returns excluding those with a graduate degree in Appendix Figure B.1. In this case, vocational majors maintain their advantage over academic majors at every age, confirming that much of the return to academic majors in the 30s and 40s comes from those who continued on to graduate study.

Figure 6: **Earnings Return: 1 Standard Deviation of Gini**

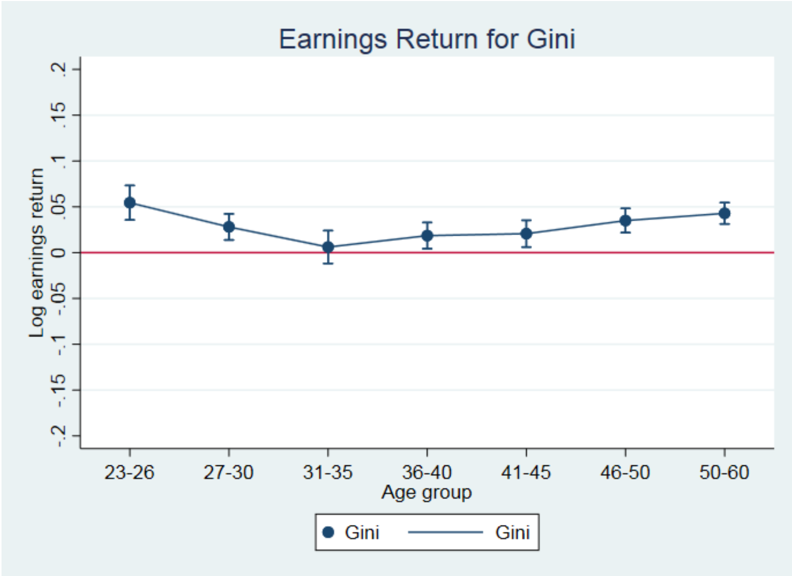


Figure 6 shows estimates for one standard deviation of the Gini measure, estimated using separate regressions by age group.[21] The positive return neer fully disappears, nearing zero in the early 30s but increasing in size and significance in the worker's 40s and 50s.

Figure 7 shows age-specific earnings estimates for the top ten and bottom ten most specific majors according to the Gini measure. The results are quite different from those of the existing measures. The most specific majors earn an initial premium of about 8%. This declines with age, and is gone by age 31-35, but the return is positive and significant again for later ages – even reaching the same level as the initial premium by age 50-60. On the other hand, general majors fare worse than average and specific majors at all ages.

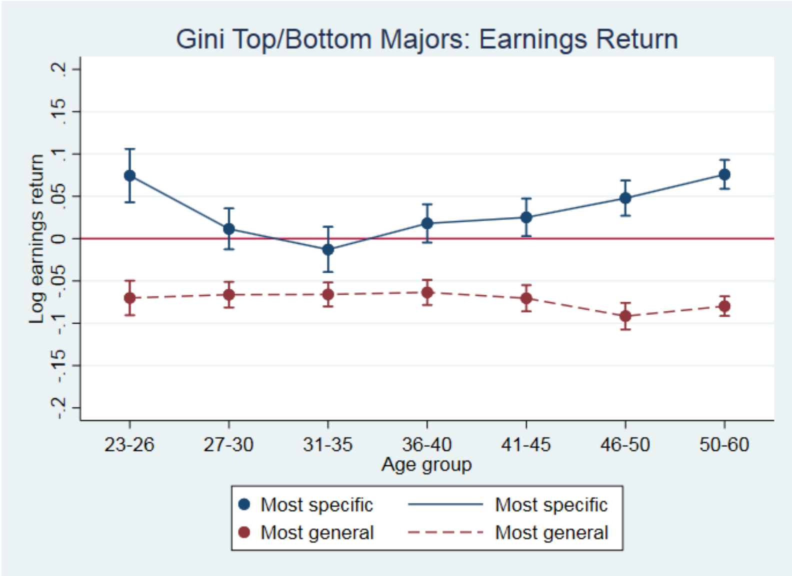
The conclusion here is different from that of vocational majors. "Academic" majors paid off more starting in the worker's 30s, giving a tradeoff between what majors were good early in the career and what majors were good later in the career. Here, there is no such tradeoff. There is no age at which it starts paying to be from a more general major. Specific majors clearly earn the most over the course of a lifetime.[22]

While Gini and the vocational measure are positively correlated, there are several key

[21] To give some context, the business major has an average Gini, primary education is about one standard deviation above the mean, and mathematics is about one standard deviation below the mean.

[22] We note that earnings is far from the only return to a major. General majors may be more enjoyable and interesting, may produce more interesting people, may produce better citizens, and may lead to more interesting jobs. These outcomes are more difficult to quantify.

Figure 7: **Earnings Return: Gini**



differences, which lead to the differing results. Four of the ten most specific majors according to Gini – finance, physics, economics, and chemistry – are not classified as vocational. These majors do not have a particular job track after college, but our measure shows that their skills are valued much more highly in some occupations than others. When we define specificity this way, we do not see the early-vs.-late career tradeoff of earnings returns.

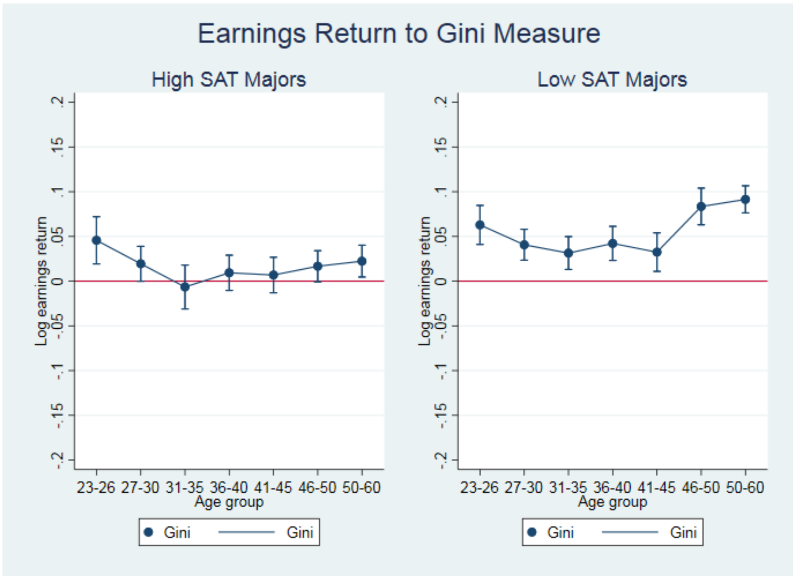
As with the other measures, we have also estimated the returns excluding those with graduate degrees. In this case, the results are nearly identical to our main results (see Figure B.1 in the Appendix). It does not seem that graduate degrees play much role in the returns to specificity as measured by the Gini coefficient.

To check if these estimates are robust to different cutoffs, we also present the Gini results for the top and bottom five majors (Figure B.2 in the Appendix) and the top and bottom third of majors (Figure B.3 in the Appendix). The deciles tell the same story as our top/bottom ten majors. The initial premium for the most specific five majors is a bit larger than to the top ten majors (13% instead of 8%), so the initial advantage of specific fields is even larger among the very most specific majors. The most general five majors consistently earn 10-15% less than average majors. The top/bottom third results still show that specific majors dominate general ones, but now the advantage over average majors is gone. This tells us that the returns to specific majors are largely concentrated in the top ten majors.

As an additional robustness check, we split the sample into two based on average SAT scores, and estimate the return to specific majors separately for the two subsamples. We do this because although our Gini measure is only weakly correlated with average SAT scores – and we control for these averages in our regressions – there may be some other characteristic of the students, correlated with earnings but not picked up by SAT, that is driving our results. While we cannot test for this directly, we can check the results separately for the high-SAT (generally high-earning) and low-SAT (generally lower-earning) fields.

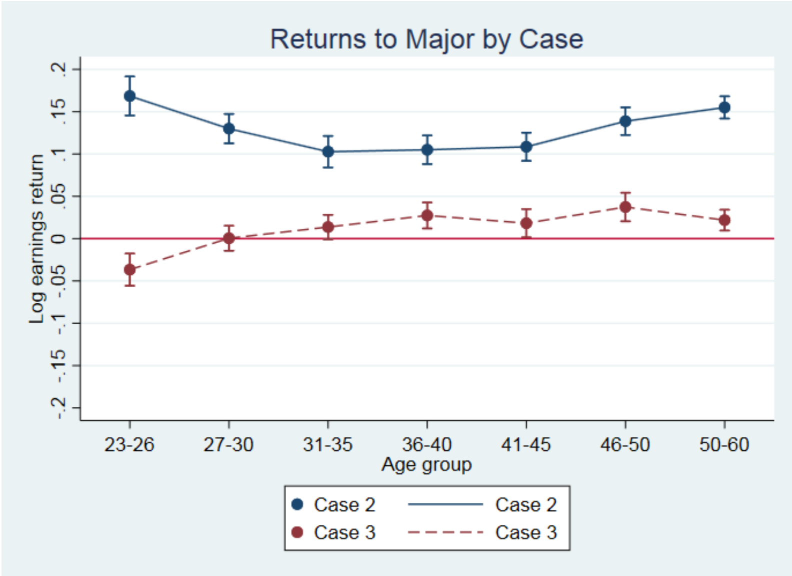
Figure 8 shows that the Gini measure has a similar initial return in the high-SAT and low-SAT subsamples, but that it is more persistent for the low-SAT majors. In both sets of majors, more specific majors see a positive earnings return at almost every age. This gives us some confidence that our results are not being driven by more specialized majors attracting students with higher average ability.

Figure 8: **High vs. Low SAT Majors**



One final question here is whether there is a difference between the earnings return to a "Case 2" major and a "Case 3" major from Figure 1. Recall that Case 2 majors have a sharply upward-sloping earnings premia graph, while Case 3 majors are highly valued in one occupation and less valued in all other occupations.

Figure 9: **Returns to Major by Case**



To see if the majors driving the earnings return to specific majors look more like Case 2 or Case 3, we (arbitrarily and by inspection of the graphs) categorize all of our majors as Cases 1, 2, or 3. We then run our earnings regressions, but instead of defining sub-sets of majors by their Gini rank, we define them by case.[23] In Figure 9, Case 1 (flat earnings premia graph) majors are the omitted group. We see here that Case 2 majors are driving most of the positive return to specificity, although Case 3 majors also earn more than Case 1 majors at most ages. This result, while only suggestive given the arbitrary nature of the exercise, is not surprising; Case 2 majors have multiple occupations in which their skills are highly valued, while Case 3 majors have only one.

Our main conclusion from these results is that there is a strong return to majors that provide specialized, less transferable skills. The initial premium is about 6% per standard deviation, and the most specific majors earn about 8% more than average majors (and 15% more than the most general majors). This premium is persistent at most ages. We do not find evidence of an early- vs. late-career tradeoff between specialization and general skills. To the degree that this trade-off is part of the conventional wisdom in thinking about specific and general education, that wisdom should be questioned.[24] On the other hand, our

[23]Results are nearly identical if we also control for the Gini measure in these regressions.

[24]Our finding of a consistent premium for specialized skills is consistent with results from Ferguson and Hasan (2013) in India.

vocational measure does replicate the early-versus-late tradeoff seen in results on vocational education in Europe (Hanushek et al. (2017), Golsteyn and Stenberg (2017)).

5.5 Evaluating the Risk of Specialized Fields

While specialized majors earn a premium on average, a natural concern is that they may be riskier than general fields. Skills that are valuable but not transferable may leave a worker vulnerable to sector-specific shocks or economic downturns, and may reduce her probability of finding employment. Because the earnings regressions only included workers with positive earnings, we also need to look at other margins to evaluate this possibility. If indeed specific majors are riskier, we would expect to see two things: first, specific majors should look worse than their average performance when looking lower in the distribution of earnings, and second, specific majors should have a lower probability of employment than general majors.

In this section, we look at these two things. First, we report results from quantile earnings regressions to evaluate whether the return to specific majors is concentrated at the top of the earnings distribution. Second, we report results for employment, hours, and wages, to break down the mechanisms behind the earnings returns.

Figure 10 shows the estimated earnings return for the top and bottom ten majors at the 20th and 80th percentiles of the earnings distribution. While estimates are imprecise, they are striking: surprisingly, the returns to specificity are stronger at the 20th percentile than the 80th, particularly in mid- and late-career. Meanwhile, the most general majors are the lowest-earning in both cases; their earnings penalty relative to average majors is consistent throughout the earnings distribution. We thus see no evidence here that specific majors are risky and more likely to have low-earning outcomes.

Figure 10: **Quantile Earnings Return: Gini**

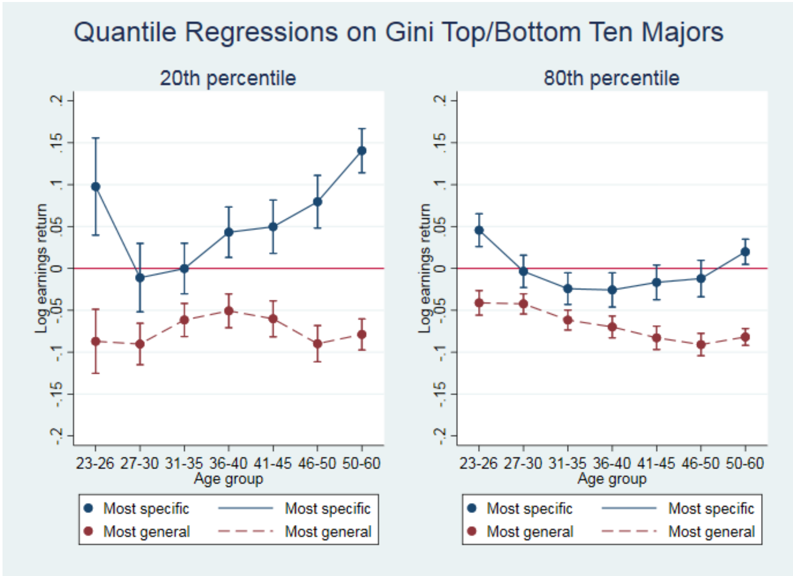
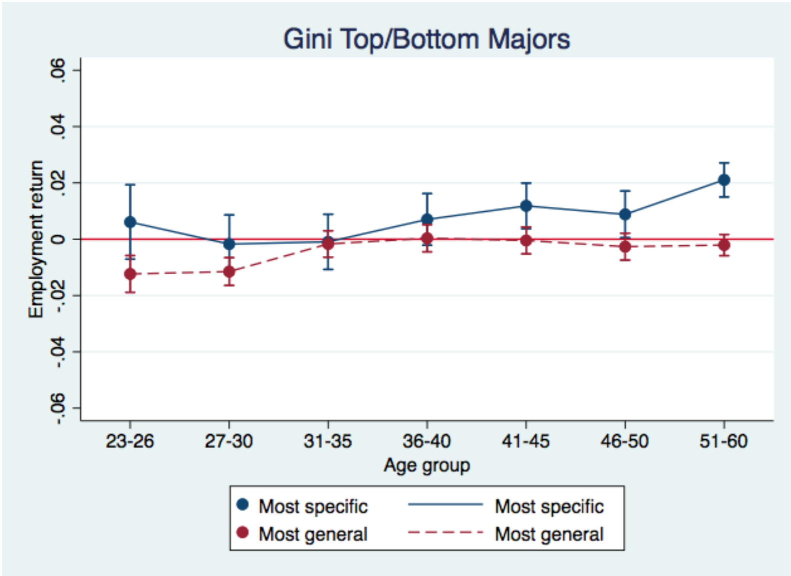


Figure 11 shows the employment probability return to majors.[25] These are probit regressions, and we graph the marginal effects; linear probability models give a similar result. Specific majors have a small, though insignificant, advantage in employment probability early in the career, and a larger advantage later. Again, there is no evidence here of specific majors being a risky bet.

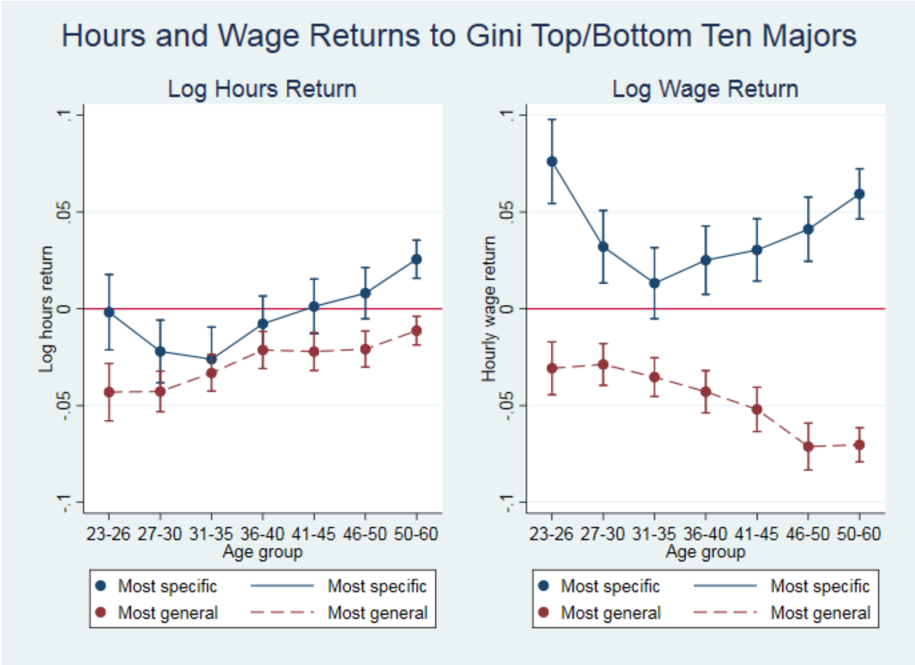
[25]To make the employment measure comparable with the other measures, we use an annual measure. We define an individual as employed if they worked at least 500 hours last year.

Figure 11: **Employment Return: Gini**



Finally, Figure 12 breaks the earnings return down into log hours and log hourly wages. Virtually all of the earnings premium for specific majors comes through higher wages, with general majors having lower wages at every age. Later in life, specific majors enjoy advantages in both hours worked and hourly wages. Meanwhile, general majors are below the average majors in hours, just as they are in earnings and wages.

Figure 12: **Hours and Wage Returns: Gini**



Overall, we see no real evidence that specific fields are riskier than general or average fields. Specific majors earn an initial premium at both the top and bottom of the earnings distribution, all of which comes through higher wages. The later-career premium is driven by an advantage at the bottom of the earnings distribution. Specific majors also do not have any employment disadvantage, although they do work slightly fewer hours than average majors.

While we cannot claim that the returns to specific majors are purely causal, our results at least suggest that students will earn more in their lifetimes from choosing specific majors rather than general majors. Why, then, would a student choose a general major? We do not model a student's objective function here, but we can think of several reasons.

First, students may not be informed about the returns to majors. Other work has shown that students' perceptions of earnings by field are often incorrect (e.g., Wiswall and Zafar (2015b)). In the case of specificity, our study is the first to report these results, so it is likely that students are not aware of the returns to specific and general majors. In light of this, risk-averse students may see more general majors as safe options.

Additionally, students may choose general majors for reasons not related to earnings.

Experimental evidence on college major choice typically finds that earnings only have a small impact on students' choices (Wiswall and Zafar (2015a)). General majors may be more interesting and enjoyable than specific majors. They also carry an option value by letting students keep their options open for the future, even if this brings an earnings penalty.

Even if the returns to specific majors are causal, it is not clear that we would want to encourage all students to choose these fields. Other research has shown that forcing students to choose majors early can lead to costly mismatch (Malamud (2010), Bridet and Leighton (2015)). A similar effect may occur here, if students who are unsure of their path are encouraged to choose specific fields. While the returns to specific and general majors are useful information for students, there are other factors to consider in thinking about students' major choices.

5.6 Entrepreneurs and Managers

An important branch of the literature on skill specificity is focused on the relationship between breadth of human capital and entrepreneurship. A prominent hypothesis, the "jack-of-all-trades" theory, predicts that those with more general skills are best suited to entrepreneurship, which requires competence in a variety of skills rather than mastery of a single skill.

Lazear (2005) pioneered this field of research by looking at Stanford Business School MBA graduates, from which he found two pieces of evidence in support of the jack-of-all-trades theory. First, those who took a more balanced MBA curriculum were more likely to become entrepreneurs, and second, the same was true of those who had held more different jobs before going to business school. Other research has shown similar findings, primarily focusing on the prior job roles held by those who become entrepreneurs (e.g., Wagner (2006)).

More recently, Lazear (2012) has advanced the importance of balanced skills for leadership within a firm. Frederiksen and Kato (2017) find evidence that human capital breadth, defined in this case as the number of prior roles, is important for securing top management positions. These papers extend the argument for broad education beyond entrepreneurs, to those holding managerial roles - regardless of whether those roles are in self-employment or not.

For data availability reasons, studying the link between the specificity of one's education and the likelihood of entrepreneurship or managerial roles is more difficult than studying the link between prior job roles and these outcomes. Lazear (2005) had access to detailed curricula for the MBA students, but this is likely not representative of the broader population. Fortunately, with our method of characterizing college degrees as specific or general, we can do this for all fields at once.

We use our Gini measure of specificity to explore the hypothesis that general education is associated with a higher probability of being an entrepreneur, or of holding a managerial occupation. Because our data do not allow us to definitively identify true entrepreneurs, we use business income as a proxy measure. We define entrepreneurs as those respondents who report income from self-employment, including negative income. Managers are defined based on occupation codes in the ACS.[26] About 16% of our observations are managers, while 9.3% are entrepreneurs.

Figure 13 repeats our primary analysis, with the dependent variable now the a binary indicator for being an entrepreneur.[27] In keeping with Lazear (2005)'s predictions, graduates from the most specialized majors are less likely than those from average majors to become entrepreneurs, with the effect increasing as workers age. However, grduates from the most general majors are not more likely than average to become entrepreneurs. There is some evidence here that specificity is negatively related to entrepreneurship, but no evidence that being very general is good for entrepreneurship.[28]

Given that only 9% of our sample reports business income (and 12% at ages 50-60), the effect associated with being in a very specific or general major on this indicator is substantial. The most specific ten majors see about a 20% reduction in the probability of being an entrepreneur at later ages (relative to average majors).[29]

Figure 14 carries out the same analysis for the probability of holding a managerial occupation. The most specialized majors are strongly negatively associated with holding managerial positions. The marginal effect of -0.03 implies about a 19% reduction in the likelihood of being a manager, which is persistent throughout the career. However, we again find no evidence that the most general majors confer any advantage with respect to the av-

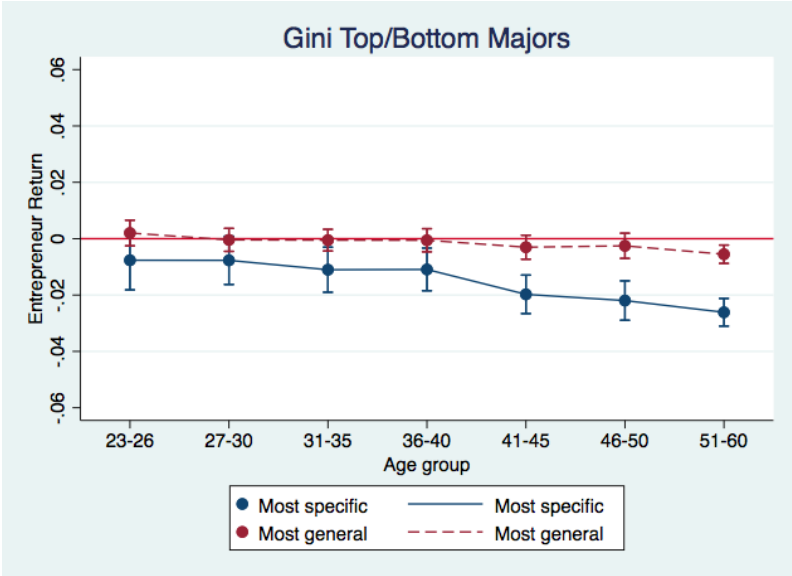
[26] We present only the results using our Gini measure here. Results for the other three measures of specificity are found in the Appendix in Figures B.4 and B.5.

[27] Unlike the earnings results, Figures 13 and 14 are results from probit regressions, and we graph the marginal effects.

[28] We have also measured entrepreneurship using an indicator for whether the person reports being self-employed. Results are similar to what we show here.

[29] A proper analysis of earnings among entrepreneurs requires its own study, but in suggestive results (Figure B.6 in the Appendix), we find that specific majors actually earn the most as entrepreneurs. It may be that while few specific majors become entrepreneurs, the ones who do are of high ability.

Figure 13: **Entrepreneurship and specificity**



erage majors. General majors have similar (low) rates of managerial jobs to those of specific majors.[30]

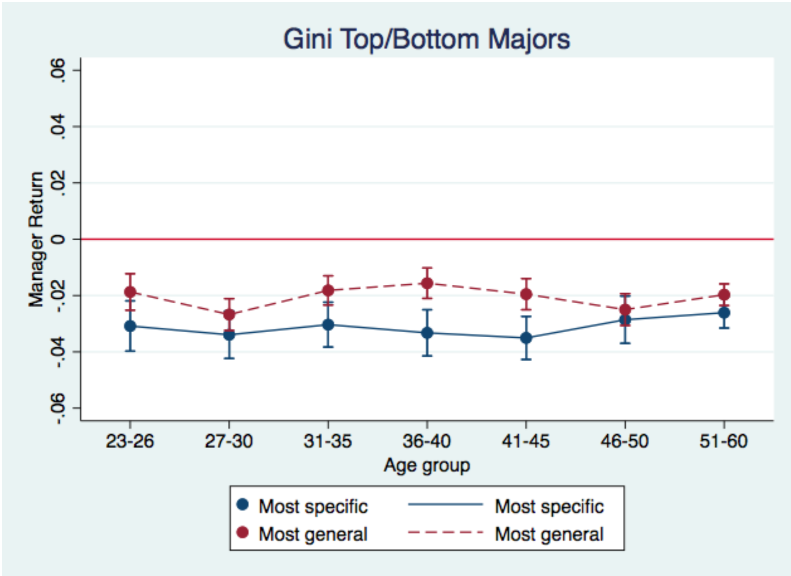
5.7 Further Applications

We have shown that our new Gini measure of human capital specificity, applied to college majors, is useful for understanding the returns to majors and in predicting particular job outcomes of graduates. Given the strong theoretical grounding of the measure in human capital theory, there are many other potential applications of our approach. We discuss some of these here, and we leave them for future research or for other researchers to explore.

First, while we have applied our measure to college majors, it can be used for other categorizations. A natural extension is to look at the differing specialization of different *levels* of education. More able workers are sometimes assumed to be more specialized than less able workers, with consequences for career paths and job mobility (Neal (1998)), while those with advanced degrees may be the most specialized of all (see Oyer (2006) for one example). While these assumptions may be valid for a measure like the occupation HHI,

[30]In Appendix Figures B.4 and B.5, we show the estimates for all four specificity measures. Note that the curriculum measure is the closest analog to Lazear's (2005) approach, but that while he was looking at individual-level specialization *within* a given field of study (MBA students), we are looking at average levels of specialization *across* fields. He also had access to individual course data, while here we are using only major-level averages.

Figure 14: **Managers and specificity**



it is not clear if it will be true for the Gini measure based on skill transferability. Any categorization of workers could be used to calculate specificity – college major, education level, education track (in countries with strong tracking systems), race, gender, and age, to name a few.

There are also obvious implications of the specificity of human capital for the careers of workers. Neal (1999) studies job mobility patterns of men and characterizes a two-stage search process, in which workers first find their occupational match and then search for the best firm match. More recently, Poletaev and Robinson (2008) and Gathmann and Schönberg (2010) study job switching patterns in detail, describing the distance of job switches by how similar the new and old jobs are in task content. These papers also show that the change in wages when workers change jobs is related to this distance.

Our notion of specificity has the potential to add a new dimension to this literature. Those with more specialized human capital should change jobs less frequently, and when they do change jobs, the changes should be smaller in terms of task content (Neal (1998)). Those with more general human capital should change jobs more often and should see larger changes in task content when they do change jobs. Further, workers with more specific human capital are likely to be hurt more by industry- or occupation-specific shocks, as their skills are less transferable to other jobs. One could thus look at the outcomes of displaced workers – as Neal (1995) and Poletaev and Robinson (2008) do – but consider differing outcomes by the human capital of the worker, rather than just the type of job change after the displacement.

The large literature studying the effect of entry economic conditions on workers' careers can also benefit from our notion of specificity (e.g., Kahn (2010), Oreopoulos et al. (2012), Altonji et al. (2016)). It is well known that a poor economy at labor market entry can have long-lasting negative effects on workers. Further, Altonji et al. (2016) show that these effects differ by college major, with higher-earning majors shielded from the worst of the effects. They also briefly investigate, in the working paper version, how the specificity of a worker's college major impacts the effect of entry conditions. Using the occupation HHI measure of specificity, they find that more specific majors earn a premium on average, but lose some of their advantage when graduating in a recession.

Our approach allows a more comprehensive investigation of this question – looking across college majors, across education levels, or some other characteristic. The direction of the effect is not obvious in theory. More general skills may shield the worker from economic downturns by allowing them to change jobs at lower cost. On the other hand, firms may retain workers with more specialized skills in a downturn at the expense of the generalists. An investigation into this question would add greatly to the literature on entry economic conditions.

6 Conclusion

The growing literature on the determinants and labor market impacts of college major choice has generated new insights on how students select their field of study, and how this choice affects earnings over the lifecycle (see Altonji et al. (2015)). Systematic differences in college major choice across genders (Brown and Corcoran (1997)) and ethnic groups (Arcidiacono et al. (2016, 2012)) make it all the more important to understand where differences in returns to field of study come from. One characteristic which differs substantially across fields of study is the level of specialization of college degrees. This paper has presented new evidence on the return to specialization in higher education, as well as shedding light on the the strengths and weaknesses of available measures used to capture educational specialization.

One of our primary contributions is developing a new way to measure the specialization of a college major, based on the transferability of skills. This aligns with the theoretical underpinnings of general and specific human capital in the tradition of labor economics. By measuring inequality of earnings premia within a major across occupations using a Gini coefficient, we identify the majors that provide specialized and general skills. We argue that this theory-driven measure has wider-ranging applications and interpretability, as compared with existing measures.

Using our preferred measure of specificity, we find that specific majors' graduates earn the most at almost every age. The initial premium is about 8% over average majors, driven entirely by higher wages. Unlike results using existing measures of specificity, there is no tradeoff between early- and late-career success. General majors always earn less than average majors. Surprisingly, specific majors do not seem to be riskier than general majors, performing well throughout the distribution and not suffering an employment penalty.

While there is a much higher return to specialized skills than to transferable, flexible skills, those from specific fields are 19% less likely than average majors to be entrepreneurs, and 30% less likely to be managers. This lends support to the prominent "jack-of-all-trades" theory of entrepreneurship and managerial ability, and suggests that our measure is capturing specialization of a similar sort to that described in that literature. However, the most general majors are not more likely to hold these positions.

The method we contribute in this paper has wide applications in labor and education contexts. The degree of specialization of a worker's education may affect her earnings, job mobility, response to shocks, and more. As the labor market changes over the coming decades, with rising automation threatening some jobs (Acemoglu and Restrepo (2017)), workers will need to have skills that can adapt to new occupations and industries. An intuitive theory would hold that those with general skills are best suited to this adjustment. While our results do not provide direct evidence on this question, they do suggest that although general skills may give a worker more options, they are not necessarily better options. Specialized skills carry not only a hefty return, but little downside risk.

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A Data Appendix

A.1 Major and occupation categories

Table A.1 lists the 51 major categories we use. For each major, we list whether the major is vocational or not (using the NCES list), and the major's rank by the occupation HHI, curriculum HHI, and Gini measures. A rank of "1" means the major is the most specific by that measure. Occupation HHI and Gini are calculated using the American Community Survey with workers aged 25-35, while the curriculum HHI is calculated from the 1993/2003 Baccalaureate and Beyond data. In the ACS, we map the field of degree variable into these 51 categories using our own crosswalk (available on request). In calculating the curriculum HHI measure, we use the total credits ("TCRED") variables to form the HHI for each major.

Table A.1: **Major Categories, with Ranks by Each Specificity Measure**

Major	Vocational?	Occ HHI rank	Course HHI rank	Gini rank
Computer Programming	Yes	10	46	1
Nursing	Yes	1	5	2
Medical Tech	Yes	7	18	3
Finance	No	17	34	4
Civil Engineering	Yes	6	4	5
Primary/General Education and Library Science	Yes	2	39	6
Chemistry	No	16	20	7
Physics	No	13	37	8
Economics	No	38	43	9
Mechanical Engineering	Yes	14	7	10
Public Administration and Law	Yes	29	17	11
Journalism	Yes	39	24	12
Commercial Art and Design	Yes	5	6	13
Other Medical/Health Services	Yes	23	21	14
Agriculture and Agr. Science	Yes	44	36	15
Secondary/Specialized Education	Yes	3	50	16
Biological Sciences	No	25	19	17
Electrical Engineering	Yes	12	11	18
Marketing	Yes	30	40	19
Public Health	Yes	47	15	20
Architecture	Yes	8	3	21
Earth and Other Physical Sci	No	22	26	22
Leisure Studies and Basic Skills	Yes	37	41	23
Protective Services	Yes	27	8	24
Business Management and Administration	Yes	43	42	25
International Relations	No	40	23	26
Chemical Engineering	Yes	20	2	27
Precision Production and Industrial Arts	Yes	15	9	28
Fitness and Nutrition	Yes	41	48	29
Political Science	No	19	22	30
Multidisciplinary or General Science	No	46	45	31
Misc. Business and Medical Support	Yes	48	47	32
Art History and Fine Arts	No	33	13	33
Foreign Language	No	28	16	34
Film and Other Arts	No	45	1	35
English, Letters, and Literature	No	36	25	36
Family and Consumer Science	Yes	24	27	37
Accounting	Yes	4	35	38
Communications	Yes	50	32	39
Social Work and Human Resources	Yes	9	10	40
Mathematics	No	18	51	41
History	No	35	28	42
Computer Science and Info Tech	Yes	11	49	43
All Other Engineering	Yes	21	12	44
Engineering Technology	Yes	31	44	45
Area, Ethnic, and Civic Studies	No	42	38	46
Environmental Studies	No	51	29	47
Philosophy and Religion	No	26	31	48
Psychology	No	34	33	49
Music and Speech/Drama	No	32	14	50
Other Social Sciences	No	49	30	51

Table A.2 lists the coarse occupation categories we use to calculate the Gini index (we exclude the 12th category: "Other/military"). These categories are taken from in the Baccalaureate and Beyond data.[31] We map the year 2000 Standard Occupational Classification (SOC) codes (Bureau of Labor Statistics (2000)) in the American Community Survey occupations into these categories, as demonstrated in Table A.2.

Table A.2: **12 Occupation Categories**

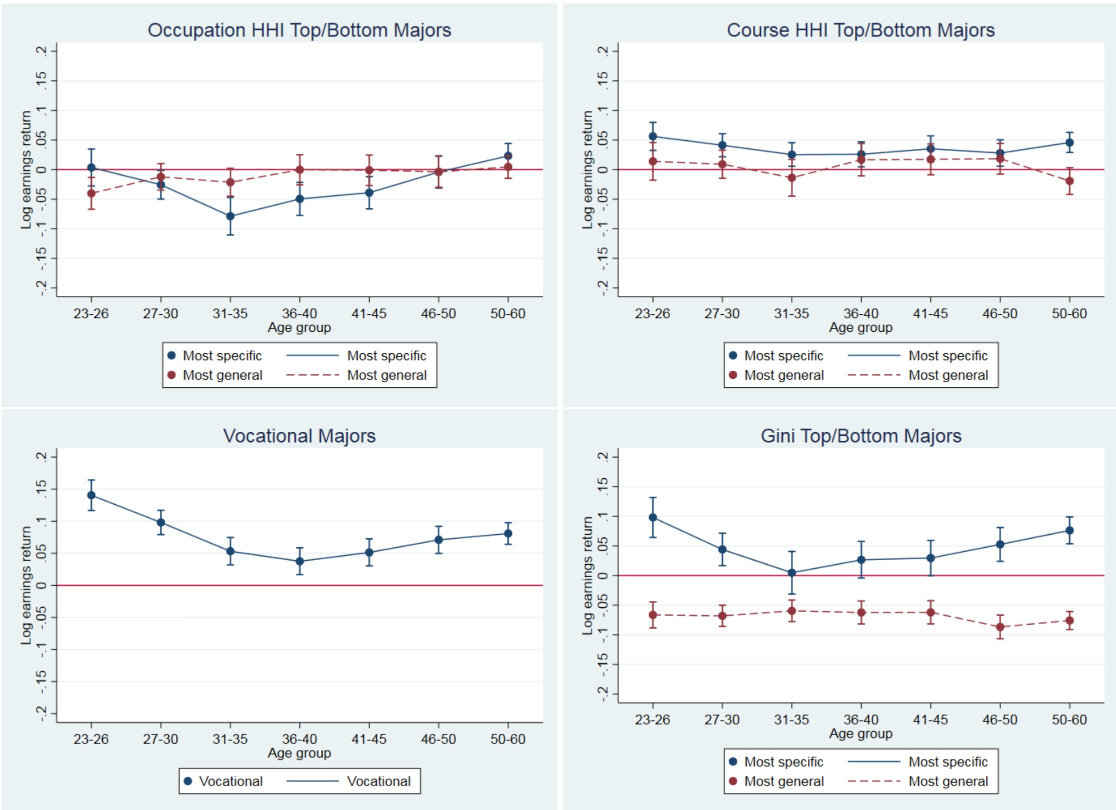
B&B Category	SOC Codes	SOC Description
1. Educators	25	Education, Training, & Library Occupations
2. Business/management	11	Management Occupations
	13	Business & Financial Operations
3. Engineering/architecture	17	Architecture & Engineering Occupations
4. Computer science	15	Computer & Mathematical Occupations
5. Medical professions	29	Healthcare Practitioners and Technical
	31	Healthcare Support Occupations
6. Editors/writers/performers	27	Arts, Design, Entertainment, Sports, & Media
7. Human/protective services/legal professionals	21	Community & Social Services Occupations
	23	Legal Occupations
	33	Protective Service Occupations
8. Research/scientists/technical	19	Life, Physical, & Social Science Occupations
9. Administrative/clerical/legal support	43	Office and Administrative Support Occupations
10. Mechanics/laborers	47	Construction and Extraction Occupations
	49	Installation, Maintenance, and Repair
	51	Production Occupations
11. Service industries	35	Food Preparation & Serving Related
	37	Building and Grounds Cleaning & Maintenance
	39	Personal Care and Service Occupations
	41	Sales and Related Occupations
	53	Transportation & Material Moving
12. Other/military	45	Farming, Fishing, and Forestry Occupations
	55	Military Specific Occupations

[31] We use the coding for the variable B3OCCAT, which is mapped to other occupation categorizations within that dataset.

B Appendix Figures

Figure B.1 replicates our earnings regressions, excluding individuals who hold a graduate degree. While access to graduate degrees, which varies across majors, should be considered part of the returns to majors, this exercise allows us to investigate the extent to which the returns estimated in Section 5 are coming from graduate-degree holders.

Figure B.1: **Earnings Return Excluding Graduate Degree Holders**



Figures B.2 and B.3 replicate our results on the return to earnings using the Gini measure, but vary the set of majors that are compared. While our main results (see Figure 7) compare the top ten most specialized majors to the bottom ten (top and bottom quintiles), we show here that the same pattern holds when comparing the top and bottom five (deciles; Figure B.2) or top and bottom 17 (thirds; Figure B.3).

Figure B.2: **Earnings Return: Deciles**

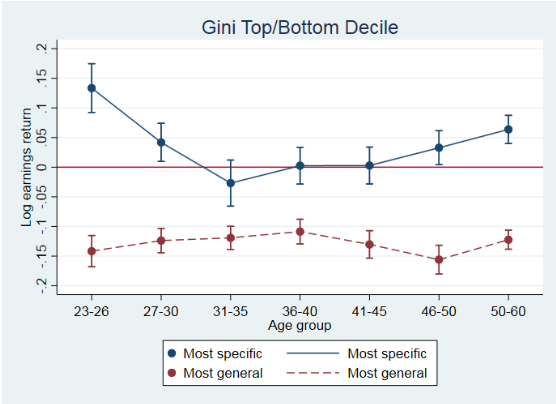
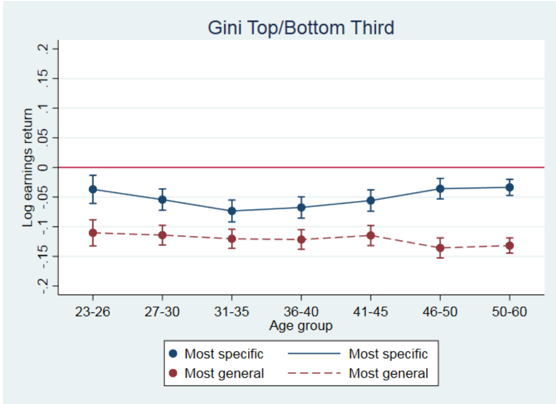


Figure B.3: **Earnings Return: Thirds**



B.1 Managers and Entrepreneurs

Our indicator for entrepreneurship is equal to 1 if the worker reports positive or negative business income. The manager indicator is equal to 1 if the worker works in a managerial occupation as defined by the ACS occupation codes. Figures B.4 and B.5 show the results of probit regressions for entrepreneurship and managerial jobs, using all four measures of specificity. We graph the marginal effects of the specificity variable in each case. These regressions also control for the variables used in the earnings regressions – race/ethnicity, gender, year dummies, a quadratic in potential experience, standard deviation of SAT scores for the major, and a cubic in average SAT math and verbal scores for the major.

Note that our measure of specific human capital is at the major level, rather than at the individual level. Our curriculum-based specificity measure therefore does not compare individuals of the same major with more or less concentrated course loads, but takes major-level averages of such measures.

Figure B.4: **Entrepreneurship and Specificity - All Measures**

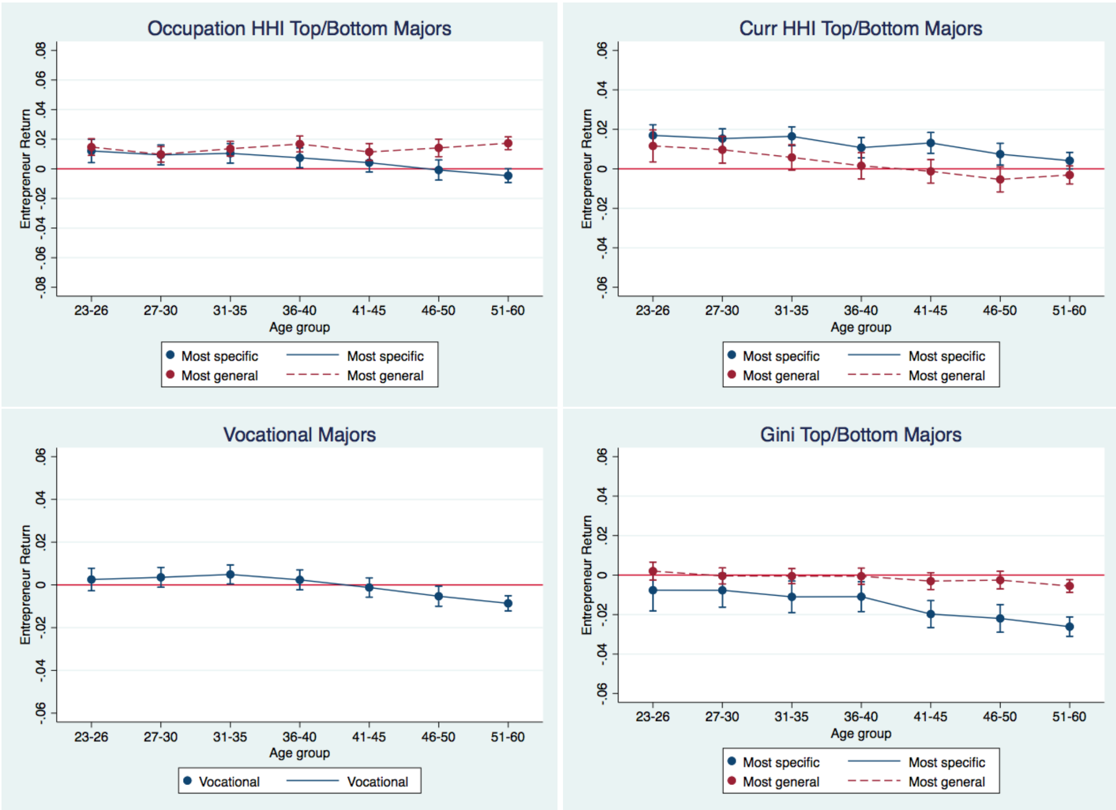


Figure B.5: **Management and Specificity - All Measures**

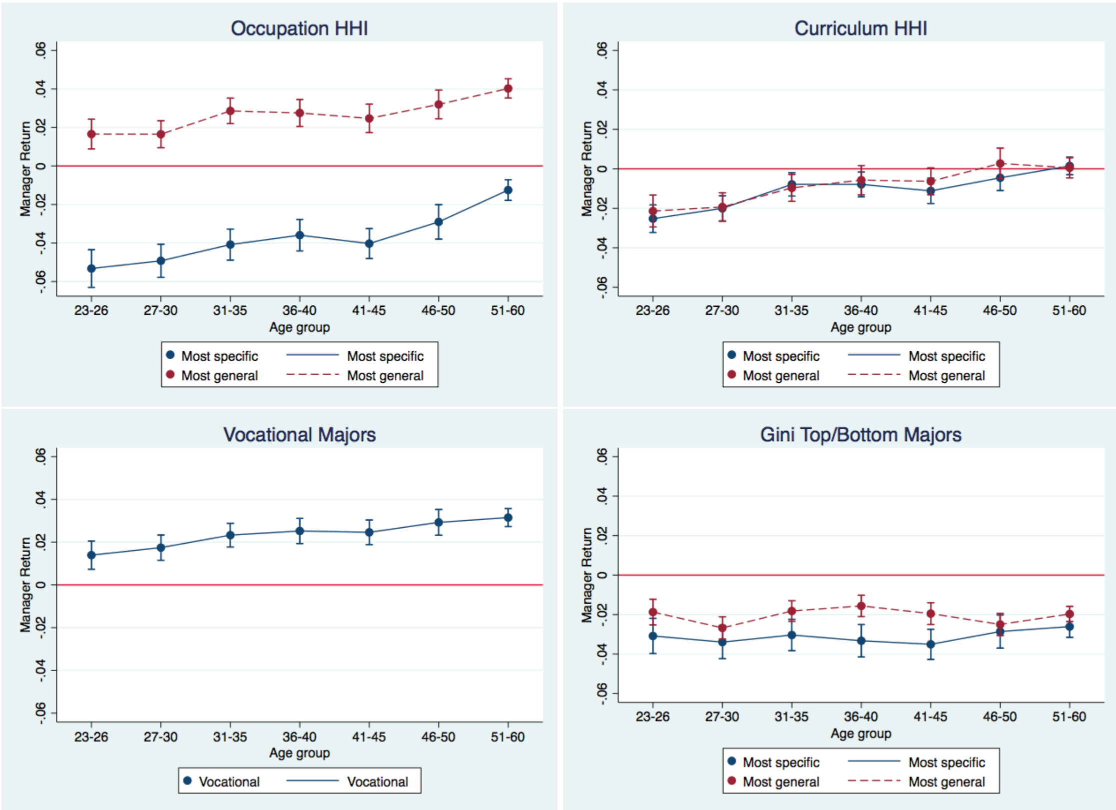
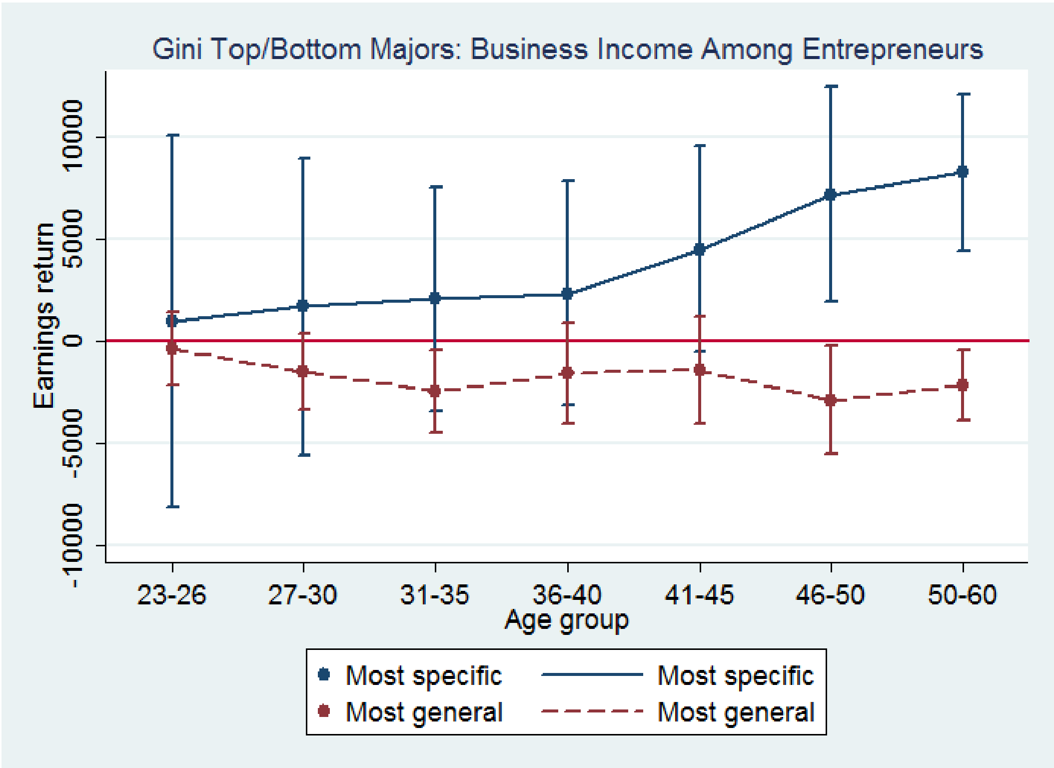


Figure B.6 shows results for business income among entrepreneurs only. Because business income can be positive or negative, we use the raw dollars rather than log income. The results show that general majors, while more likely to be entrepreneurs, earn less when they are entrepreneurs.

Figure B.6: **Business Income Return Among Entrepreneurs**



C Extended Results

Table C.1: **Log hours**

	(1) log hours	(2) log hours	(3) log hours	(4) log hours	(5) log hours	(6) log hours	(7) log hours	log hours
Occupation HHI	-0.001***	0.003*						
	(0.000)	(0.001)						
Occ HHI*potexp		-0.001***						
		(0.000)						
Occ HHI*potexp^2		0.000***						
		(0.000)						
Curriculum HHI			-0.008***	-0.006***				
			(0.001)	(0.002)				
Curr HHI*potexp				-0.001**				
				(0.000)				
Curr HHI*potexp^2				0.000***				
				(0.000)				
Vocational					0.013***	0.052***		
					(0.001)	(0.004)		
Vocational*potexp						-0.004***		
						(0.000)		
Vocational*potexp^2						0.000***		
						(0.000)		
Gini							0.007***	0.014***
							(0.001)	(0.004)
Gini*potexp								-0.001***
								(0.000)
Gini*potexp^2								0.000***
								(0.000)
Constant	11.882***	11.879***	12.184***	12.124***	11.772***	11.870***	11.547***	11.518***
	(0.593)	(0.593)	(0.590)	(0.591)	(0.587)	(0.587)	(0.585)	(0.585)
Observations	2,731,272	2,731,272	2,731,272	2,731,272	2,731,272	2,731,272	2,731,272	2,731,272
R-squared	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is log annual hours worked, defined as weeks worked times usual hours of work. All regressions also include gender, race, a quadratic in potential experience, year dummies, a cubic in average SAT Math and Verbal scores in the major, and the standard deviation of SAT scores in the major. Data: ACS 2009-2015, college graduates aged 23 to 60.

Table C.2: **Log Wages**

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage	(6) log wage	(7) log wage	log wage
Occupation HHI	0.018***	0.071***						
	(0.000)	(0.001)						
Occ HHI*potexp		-0.006***						
		(0.000)						
Occ HHI*potexp^2		0.000***						
		(0.000)						
Curriculum HHI			0.002**	0.005*				
			(0.001)	(0.002)				
Curr HHI*potexp				-0.001***				
				(0.000)				
Curr HHI*potexp^2				0.000***				
				(0.000)				
Vocational					-0.018***	0.127***		
					(0.002)	(0.005)		
Vocational*potexp						-0.014***		
						(0.001)		
Vocational*potexp^2						0.000***		
						(0.000)		
Gini							0.023***	0.042***
							(0.002)	(0.005)
Gini*potexp								-0.003***
								(0.001)
Gini*potexp^2								0.000***
								(0.000)
Constant	20.518***	20.679***	19.276***	19.143***	19.595***	19.836***	17.875***	17.851***
	(0.705)	(0.705)	(0.699)	(0.700)	(0.696)	(0.696)	(0.696)	(0.696)
Observations	2,598,334	2,598,334	2,598,334	2,598,334	2,598,334	2,598,334	2,598,334	2,598,334
R-squared	0.138	0.138	0.137	0.137	0.137	0.138	0.138	0.138

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is log hourly wage, defined as total wage and salary earnings divided by hours worked. All regressions also include gender, race, a quadratic in potential experience, year dummies, a cubic in average SAT Math and Verbal scores in the major, and the standard deviation of SAT scores in the major. Data: ACS 2009-2015, college graduates aged 23 to 60.

Table C.3: **Employment (Probit)**

	(1) employed	(2) employed	(3) employed	(4) employed	(5) employed	(6) employed	(7) employed	employed
Occupation HHI	0.035***	0.017***						
	(0.001)	(0.003)						
Occ HHI*potexp		0.001***						
		(0.000)						
Occ HHI*potexp^2		-0.000**						
		(0.000)						
Curriculum HHI			0.021***	0.038***				
			(0.002)	(0.006)				
Curr HHI*potexp				-0.002***				
				(0.001)				
Curr HHI*potexp^2				0.000***				
				(0.000)				
Vocational					0.046***	0.044***		
					(0.004)	(0.012)		
Vocational*potexp						0.002		
						(0.001)		
Vocational*potexp^2						-0.000**		
						(0.000)		
Gini							0.018***	-0.016
							(0.004)	(0.014)
Gini*potexp								0.003**
								(0.001)
Gini*potexp^2								-0.000
								(0.000)
Constant	3.302**	3.252**	0.815	0.834	0.405	0.321	-0.665	-0.713
	(1.558)	(1.558)	(1.541)	(1.541)	(1.544)	(1.545)	(1.542)	(1.542)
Observations	3,052,655	3,052,655	3,052,655	3,052,655	3,052,655	3,052,655	3,052,655	3,052,655

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

These are probit regressions. The dependent variable is a dummy variable for working at least 500 hours in the prior year. All regressions also include gender, race, a quadratic in potential experience, year dummies, a cubic in average SAT Math and Verbal scores in the major, and the standard deviation of SAT scores in the major. Data: ACS 2009-2015, college graduates aged 23 to 60.