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. To measure specificity, 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. Education and nursing are the most specific majors, while philosophy and psychology are among the most general. Using data from the American Community Survey, we find that the most specific majors typically pay off the most, with an early-career earnings premium of about 5-6% over average majors (15-20% over the most general majors), driven by higher hourly wages. General majors lag far behind at every age. Despite their earnings advantage, graduates from specific majors are the least likely to hold managerial positions, with graduates from majors of average specificity being the most likely to do so. It may be that managerial positions require a mix of specific knowledge and broadly applicable skills.

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1 Introduction

The existence of large differences in earnings across graduates from different majors is 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. Majors differ along many dimensions – student ability, course requirements, and quantitative content, for example – all of which may affect earnings returns.

In this paper, we study the role of the level of specialization of college majors. Some majors provide highly specific skills, while others provide general, transferable skills. We conceptualize and measure this specificity using a novel approach, and then estimate the return to specialized and general college degrees over the life cycle.

College major specialization is of particular interest for three 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. Second, the growing literature on the correspondence between education and occupation has important insights for understanding the return to college majors.[2] Third, the specificity of a field of study plays a central role in a prominent literature on entrepreneurship and managerial jobs (e.g., Lazear (2005)). In this literature, entrepreneurship requires general skills, while wage earners may be more specialized. This idea has yet to be investigated at the college major level.

We first summarize previous approaches to measuring educational specificity, which are useful but have little basis in human capital 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)). The specificity of human capital is determined by its transferability – 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 approach produces intuitive results: education and nursing are the most specific majors, while

[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. (2018) 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.

psychology, music, and philosophy are among the most general. But it also shows that some majors usually considered "specific" actually produce graduates with highly versatile skills (e.g., accounting).

We then apply our new measure to two empirical questions. We first estimate the earnings returns to college major specificity. We find that specific majors enjoy an earnings premium throughout most of the life cycle. At the start of their careers, these majors earn about 5-6% more than average majors and 15-20% more than the most general majors. The premium for the most specific majors is smaller at later ages, but still usually positive. The most general majors, which provide transferable skills, lag behind at all ages. The earnings effect operates entirely through hourly wages and not through hours worked or employment probabilities. These findings contrast with the returns given by some existing measures of specificity, which typically show an early-career premium and a later-career penalty.

The second empirical question we address concerns managers and entrepreneurs, as we investigate the predictions of the "jack-of-all-trades" hypothesis developed by Lazear (2005). Surprisingly, we find that specific majors are slightly more likely than average majors to become entrepreneurs early in the career. However, despite the advantage of specific majors in average earnings, these majors are associated with much lower probabilities of entering management occupations at all ages. Majors which are neither very general nor very specific are by far the most likely to become managers. It may be that management requires a balance between general skills and specific expertise.

There have been various approaches to measuring specialization in higher education and its returns in the labor market. Much of this literature focuses on countries with a well-defined vocational track (e.g., Hanushek et al. (2017), Golsteyn and Stenberg (2017), Silliman and Virtanen (2019)). The vocational-academic distinction is less clear in the US, and certainly less clear when looking at 4-year college majors. Other measures of the specificity of educational programs include occupation-based measures (e.g., Blom et al. (2015), Altonji et al. (2012)), curriculum-based measures (e.g., Silos and Smith (2015), Lazear (2005)), and self-reported match between field and job (e.g., Kinsler and Pavan (2015)). All of these are useful in different contexts, but all have weaknesses. Except for vocational programs, little is known about the returns to specific fields of study.

We make three main contributions to the literature. First, we develop a new theory-driven measure of college major specificity, and in doing so provide a methodology that could be applied to other contexts. We then make two empirical contributions. We provide the first estimates of the earnings return to specific and general college majors, showing that the most specific majors outperform the most general majors at all ages. We then provide the first cross-major evidence on Lazear's (2005) theories of entrepreneurship and management.

The remainder of the paper proceeds as follows. In Section 2, we review the measures that have previously been used to capture the specialization of higher education programs. In Section 3, we introduce our new measure of major specificity, a modified Gini coefficient of earnings inequality across occupations. In Section 4, we compare our measure of specificity to various other options using a range of data sources. In Section 5, we estimate the earnings return to specificity, look at some specific job outcomes, and discuss further applications. Section 6 concludes.

2 Measuring Specialization: Previous Approaches

While many papers have conceptualized general and specific human capital in a variety of settings, there is no consensus on what specificity means or what it is supposed to measure. In this section, we describe some of the previous approaches and explain why each one is imperfect. We follow this with our own measure in Section 3, which attempts to improve on these existing measures.

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) define 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 (e.g., Rakitan and Artz (2015)).

Lazear (2005) uses the "lopsidedness" of curricula taken by MBA students as a measure of how specific or general their training is. 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.

The data requirements of the curriculum approach are formidable, requiring college transcript data for students in each major. Even if one has this, it is not obvious that all college courses are equally broad. Suppose the average education major takes 50% of her courses within the education department, while the average mathematics major takes 50% of her courses within the mathematics department. Their curriculum is equally "specialized", but education courses could be broader in scope than mathematics courses, so the measure could be misleading. It could also be misleading if some skills are more widely useful than others. A journalism degree might be classified as specific by curriculum, but writing may be a skill which is valued in a wide range of occupations.

2.2 Labor Market Orientation of Degree Program

Another approach is to use the closeness of the link between the field of study and the labor market. The most common of these is the "vocational" versus "academic" dichotomy (see, e.g., Hanushek et al. (2017), Brunello and Rocco (2017) and Golsteyn and Stenberg (2017)). This classification of programs is most common in countries with established vocational education tracks, although Kreisman and Stange (2017) and Stevens et al. (2019) use similar approaches with US high school and community college data, respectively.

Using a binary measure like this is imperfect if some vocational programs are more specialized than others (Coenen et al. (2015)). For instance, Hall (2013) studies a reform in Sweden that extended and expanded the general content of vocational secondary school (Hall (2013)).

While applications of the vocational approach to four-year college majors are rare, Saniter and Siedler (2014) classify majors as being labor market oriented if they lead to a particular profession. Bridet and Leighton (2015) do something similar using a restricted set of majors. This is a useful idea, but vocational-based measures are typically reliant on perceived, rather than empirical, relations between majors and occupations. They also miss much variation across majors. The Department of Education, for example, classifies both business and education as vocational majors, though most observers would consider education to be the more vocational major.

2.3 Measures Based on Job Outcomes

A third family of measures of specialization, popular in empirical studies, defines specificity using job outcomes. Blom et al. (2015) compute major-specific measures of occupational concentration using a Hirschman-Hirfindahl Index (HHI). Majors which send most of their graduates to a single or small number of occupations are considered specialized, while those that send graduates evenly across many occupations are general. Altonji et al. (2012) calculate the share of graduates from each major who are employed in the three most popular occupations for that major.

This type of measure may be the most intuitive of the existing approaches. Its main weakness is not incorporating earnings information. Just because the skills of a major are typically applied in only a few occupations does not mean that they are not rewarded in other occupations. Engineering majors typically become engineers, but given their strong analytical skills, they may also be highly productive in finance or consulting. To know this, we would need to look at how the engineering majors who do enter those other occupations perform. We can improve on the occupational specificity measure by incorporating earnings of graduates in these "atypical" occupations for their major.

Finally, job outcomes can be used along with self-reported information on how strongly a job is related to the worker's field of study. Examples of this approach include Borghans and Golsteyn (2007), Kinsler and Pavan (2015), and Coenen et al. (2015). If a major earns much more in "related" jobs than in "unrelated" jobs, it can be considered specific. This is an improvement on other methods because it uses earnings information; we draw on a similar logic for our measure.

3 A Theory-Driven Measure of Specialization

While these existing approaches have their merits, none fully captures the notion of specificity as described in the tradition of labor economics. Becker (1962) 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.

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's graduates may only have a few skills, but if those skills are valued everywhere, then they are highly 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.

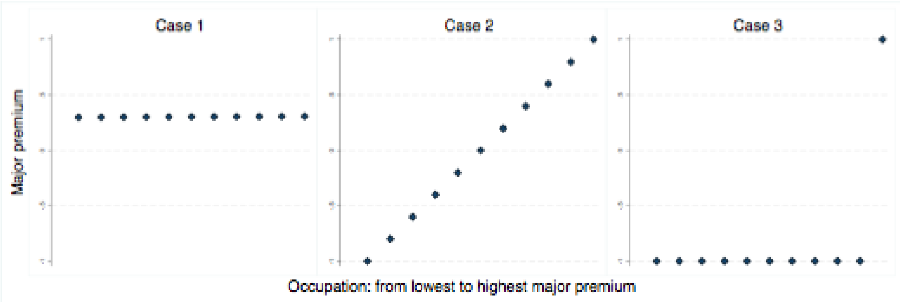
The existing measures of specialization lack two key things. First, they do not use earnings information in defining specificity, which is essential to measure the value of skills. Destination occupation and course content are inadequate without information on the value of skills. Second, they lack the 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, drawing on literature that finds occupation-specific human capital to be more important than industry in most cases (e.g., Kambourov and Manovskii (2009), Bana (2018)). A general major is one whose graduates perform equally well across occupations; their skills are valued in a similar manner in 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.

The graph of hypothetical Case 1 (the 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

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



SOURCE: simulated data.

major. A perfectly flat set of dots would mean that the graduates earn exactly the same return in every occupation, relative to the average major in that occupation. The flatter the dots, the more general the major is. The level is not relevant here: we would consider a major whose graduates perform very poorly in all jobs *or* very well in all jobs to be general.

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.

While there are various inequality measures available, the Gini coefficient is a natural choice.[3] In addition to being a familiar and widely used measure, it also has some desirable

[3] See Cowell (2000) for an excellent introduction to the literature on measuring inequality.

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 in order 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 factors for which we have information, and includes survey year and 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.[4] We interpret the coefficients on the major fixed effects as that major's premium (net of other covariates) in that occupation. Formally, for each occupation we regress:

$$ln(earn)_{im} = \beta_0 + X_i\Gamma + year_i + m_i + \epsilon_{im} \tag{1}$$

where the X_i includes gender, race/ethnicity, and a quadratic in potential experience (year minus implied year of college graduation). The dependent variable is log wage and salary income for the year, in constant dollars. To estimate the major effects consistently across occupations, we constrain the effects of race, gender, and potential experience to be the same across all occupations.[5]

The major fixed effects m_i give the earnings premium, net of demographics, for each major in each occupation. We use 51 majors and 11 occupations, so we estimate Equation 1 eleven times, and estimate 51 major premia from each regression.[6] 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

[4]Our results are robust to weighting all observations equally.

[5]Allowing these coefficients to vary across regressions yields nearly identical results. Including Census division fixed effects and division-by-year fixed effects also has no effect.

[6]We use the 11 occupations given in Table A.2 (excluding "Other/military"), taken from the broadest categories in the Baccalaureate and Beyond. Our procedure depends on having enough observations in each major-occupation cell, which requires this broad grouping. We discuss the robustness of this choice in Appendix A.2.

compute a Gini coefficient for each major, as follows:

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

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. To reduce the influence of small (and therefore imprecisely estimated) cells on our final measure, we weight each set of absolute deviations by w_k, the share of observations from major m in occupation k. This weighting affects the majors for which employment is concentrated in a small number of occupations, but does not make much difference for our earnings results given in Section 5. Note that this is an "absolute" Gini measure, which makes the measure level-invariant.[7]

To connect our empirical measure with the intuition that drove it, we now 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 philosophy/religion on the left, finance and nursing in the middle, and our two education majors on the right.[8]

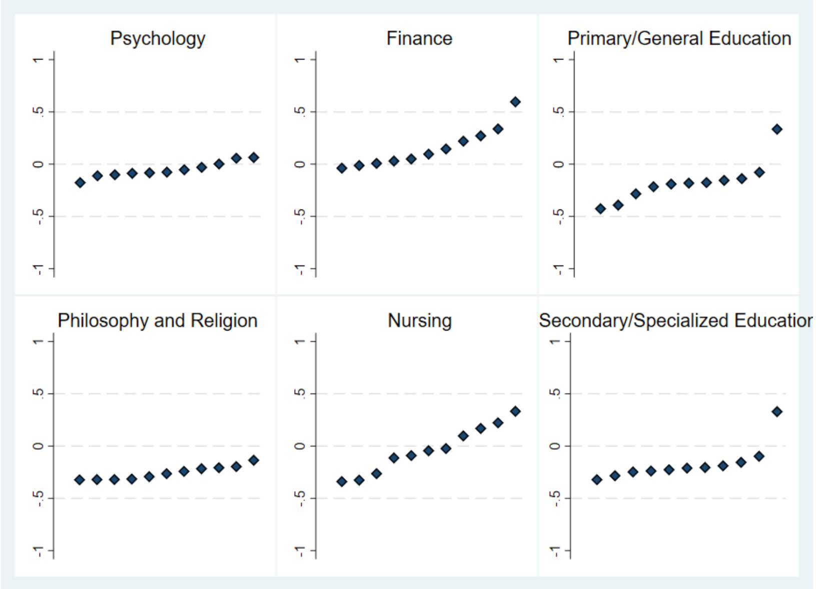
Psychology and philosophy/religion look much like Case 1 from Figure 1. The relatively flat lines mean that graduates of these majors earn similar premia in each occupation. Psychology earns a premium near the average permium for every occupation, while philosophy/religion is somewhat below average everywhere. These are therefore general majors, with skills valued similarly across occupations. Both are among the five most general majors according to our Gini measure.

Finance and nursing look similar to hypothetical Case 2, earning higher returns in some occupations than others. 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.

[7]The "relative" Gini, used to compute nations' income inequality, would divide by the average premium for the major across occupations, which is often very close to zero and sometimes negative. The relative Gini is 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; it also accommodates negative values, allowing us to use de-meaned major premia.

[8]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**



SOURCE: Authors' calculations from regressions using the ACS 2009-2015.

The four majors on the right of Figure 2 are all rated as very specific by our Gini measure. The two education majors are the two most specific majors, followed by nursing. Finance is the seventh most specific. 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.[9]

Our approach is distinct from that of other papers also focused on specificity of educational programs. Borghans and Golsteyn (2007), Kinsler and Pavan (2015), and Coenen et al. (2015) all use self-reported information on how strongly the job is related to the worker's field of study. For instance, in Kinsler and Pavan (2015), the larger the premium for being in a "related" job, the more specific the college major is.

Our approach has a similar flavor, but we let the earnings premia tell us how related the major is to the occupation, rather than relying on self-reports. While both approaches are valuable, it may be difficult for graduates to know how related their job is to their major. Economics majors, for example, may learn analytical and critical thinking skills that are valuable in many jobs, even if the subject matter of the job does not *seem* related to

[9]A list of the most specific and most general majors is found in Table 4, and the complete ranking of majors is in Table A.1.

economics. Workers' perceptions may not always line up with what the data tell us. Looking at earnings premiums gives a more objective measure of how those skills are valued in each occupation.

Perhaps unsurprisingly, our measure is sensitive to the level of aggregation of both majors and occupations. When more aggregated major categories are used, general and specific majors are often lumped together. For example, a "STEM" major category typically includes both general majors such as mathematics (ranked 43rd out 51 majors) as well as specialized ones like biology (11th) and civil engineering (12th). Aggregating STEM subjects will produce a major that appears to be only moderately specific - a substantial change for many of the component majors. We provide a more detailed discussion of these issues in Appendix A.2.

The calculation of our measure relies on having sufficient data to estimate a premium for each major in each occupation. If majors are too small to get precise estimates of the earnings premium within each cell, the resulting specificity measure could be inaccurate. While our weighting technique helps stabilize the calculation of the measure for majors that have some small occupation cells and some large ones, it does not solve the problem of majors with many small cells - and therefore many noisily estimated premia. We have performed simulations showing that this issue is unlikely to lead to substantial errors in our empirical work, but in applications with smaller data sets, more aggregation of majors may be needed.

3.1 Dealing with Selection

A potential issue with our approach is selection of graduates across occupations in a given major.[10] If more able students from a major choose certain occupations, then they will likely earn more than other graduates from that major. If there is more cross-occupation selection for some majors than for others, then the majors with the most selection will have greater earnings inequality across occupations and will thus look more specific. It is difficult to rule this out without measures of individual ability.

Faced with this concern, we perform three exercises to validate our approach. First, we calculate the Gini measure without including demographic measures in Equations 1.

[10] The ideal way to measure skill transferability would be to randomly assign graduates to occupations. Absent this possibility, one could look at the change in wages for occupation switchers. However, switchers are also a highly selected group, and the destination occupations would be endogenous. Our approach is more feasible.

If selection on these observable measures is important, this should change the ranking of majors. We are encouraged by the fact that the Gini produced by this approach is correlated at 0.97 with the one including demographics, and the ranking of majors is largely unchanged.

Second, we use the restricted-use Baccalaureate and Beyond (B&B) 08/12 data, which contains individual-level SAT scores, to compute the Gini coefficient for majors with and without these test scores included as a control for ability. If selection on cognitive ability is a substantial issue, one would expect the two approaches to give different rankings of majors. A weakness of using this dataset is that its small sample size requires us to use only 11 majors and 5 occupations to avoid empty cells.

Results are in Panel A of Table 1. The two Ginis - with and without individual SAT math and verbal scores - are correlated at 0.99, and the rankings of majors are almost identical. This occurs because in the B&B regressions, once major fixed effects are included, SAT scores have no significant impact on earnings. In both cases, education, engineering, and health are the most specific majors, while social sciences are the most general.

Table 1: **Validation Exercises**

Panel A: Using Baccalaureate and Beyond Data

Major	**Gini with SAT**	**Rank with SAT**	**Gini without SAT**	**Rank without SAT**
Education	0.118	1	0.118	1
Engineering/arch/comp sci	0.107	2	0.107	2
Health majors	0.075	3	0.068	3
Soc. work/protective service	0.058	4	0.057	4
Math/physical sciences	0.048	5	0.054	5
Business	0.044	6	0.043	7
Communications/journalism	0.043	7	0.040	9
Arts	0.039	8	0.045	6
Humanities/liberal studies	0.037	9	0.042	8
Biological sci/agriculture	0.026	10	0.030	10
Social sciences	0.019	11	0.018	11
Correlation in Ginis	0.99			
Correlation in ranks	0.95			

Panel B: Comparing ACS to Expectations Data from Arcidiacono et al. (2017)

	ACS Age 31-33 Data		Expectations Data	
Major	**Gini**	**Rank**	**Gini**	**Rank**
Natural sciences	0.061	1	0.053	1
Engineering	0.060	2	0.040	3
Public policy	0.049	3	0.038	4
Economics	0.046	4	0.048	2
Humanities	0.044	5	0.026	5
Social sciences	0.036	6	0.016	6
Correlation in Ginis	0.78			
Correlation in ranks	0.83			

NOTE: Panel A reports Gini coefficients calculated from the Baccalaureate and Beyond 08/12 data. They are computed with SAT math and verbal scores and then without. Regressions are at the occupation level (6 occupations) and also include race and gender. All people in the sample are 4 years out of college. Panel B reports unweighted Gini coefficients calculated on 6 occupations and 6 majors from the ACS and from the expectations data in Arcidiacono et al. (2017).
SOURCE: Panel A uses the restricted Baccalaureate and Beyond 08/12 data. Panel B uses data from the American Community Survey and expectations data from Arcidiacono et al. (2017).

Third, we make use of earnings expectations data from Arcidiacono et al. (*Forthcoming*; Table A3). Undergraduate students were asked to give their expected earnings in six broad majors and six occupations (or 36 total major-occupation combinations). Because every student gave their expected earnings for every major-occupation pair, the data are "selection-free": we observe every student's expectation in every cell, instead of only the one they end up choosing.

Using these data, we compute a variant of our Gini measure using the six majors and six occupations from Arcidiacono et al. (Forthcoming).[11] We compute it two ways, first using the expectations data (free of selection) and then using the actual

[11] The data given in the paper are aggregated at the major-occupation level, which prevents us from applying the exact method we describe in Section 3. We use the occupation-demeaned log of expected income in place of the regression coefficient, and we set all the occupation-major weights equal to 1.

ACS data for those majors and occupations (with potential selection).[12] The results are in Panel B of Table 1. The correlation between the ACS Gini and the expectations data Gini is 0.78, and five of the six majors are ranked in the same order. Sciences and engineering are ranked as specific by both, while social sciences are always general. Only economics changes rank, appearing more specific in the ACS data than in the expectations data. This may reflect the fact that students do not always know what jobs one does with an economics degree.[13]

These three exercises provide evidence that patterns of selection of individuals to occupations are not driving the differences in specificity we find across majors. While we cannot control for selection directly in the ACS, we do not expect that doing so would substantially change either the ranking or the individual Gini coefficient for most majors.

4 Empirical Comparison of Measures

Here we briefly compare our Gini measure to measures representing the three previous approaches: curriculum, labor market orientation, and occupational outcomes. A full comparison of the majors across the various measures is available in Table A.1.

4.1 Definition of Other Measures

In addition to our Gini measure of specificity, we construct three others for comparison. First is an occupational Hirschman-Herfindahl Index (HHI), as used by Blom et al. (2015), to measure the specificity of majors according to destination occupation. We again use data on individuals aged 25 to 35 from the 2009-2015 ACS, as we did with the Gini coefficient. The HHI is calculated as follows:

[12]The students are asked to give earnings 10 years after graduation, so in the ACS we restrict here to age 31 to 33.

[13]Interestingly, the Gini coefficients computed from the expectations data are almost all smaller (more general) than the actual data. It could be that students overrate the generality of majors, or it may be that degrees from elite universities (these data were collected at Duke) are more transferable than equivalent degrees from a lower-ranked university.

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

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 this measure in standard deviations for ease of interpretation.[14]

Second is a measure of how specialized a major's curriculum is. We construct an HHI of courses taken for each major using transcript data from the restricted version of the 1993/2003 Baccalaureate and Beyond (B&B) dataset:

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

where m denotes the major, f denotes a coarse grouping of fields of study,[15] and s_{mf} denotes the average share of undergraduate credits (not courses) earned in field f by students graduating from major m. We also put this measure in standard deviations.

Finally, we construct a binary "vocational" or "academic" classification of majors using a taxonomy from the National Center for Education Statistics.[16] While the US does not have well-defined vocational tracks at the unviersity level, it is still interesting to try to compare our Gini with such a measure. Majors such as engineering, accounting, and education are classified as vocational, while humanities, social sciences, and mathematics are among the academic majors. Table A.3 in the Appendix shows the full list of majors classified as vocational and academic.

[14]This is highly correlated with 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).

[15]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.

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

4.2 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 majors by each measure.

Table 2 presents correlations between the measures, as well as correlations between each measure and three major-level test score measures: average SAT Math scores, average SAT verbal scores, and the standard deviation of SAT scores in the major.[17] All four specificity measures are positively correlated. The Gini is most correlated with the occupational HHI measure ($\rho = 0.69$): this is partly mechanical given that we used occupation-major cell size weights in our Gini calculation. The Gini is also positively correlated with the vocational indicator, but only weakly correlated with the curriculum HHI measure ($\rho = 0.04$). It is slightly negatively correlated with average SAT scores.

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	0.686	1.000					
Curr HHI	0.043	0.217	1.0000				
Vocational	0.375	0.336	0.122	1.000			
SAT M	-0.103	-0.146	0.197	-0.189	1.000		
SAT V	-0.298	-0.261	0.185	-0.474	0.719	1.000	
SAT St Dev	-0.185	-0.220	-0.006	-0.193	0.021	0.248	1.000

SOURCE: The Gini and occupation HHI are calculated using the ACS. The vocational categorization is adapted from the NCES postsecondary taxonomy. The curriculum HHI is calculated from the restricted-use Baccalaurate and Beyond data, which is also the source of the average SAT variables by major.

The top and bottom ten majors for each measure are shown in Table 3. While there is some broad agreement across measures – nursing is specific by any measure – the lists are quite different. Education has a general curriculum, but produces the most specialized skills according to our measure. Accounting is very general according to the Gini measure, despite being very specific by occupation HHI.

[17] These correlations weight all majors equally.

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

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

NOTE: 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.
SOURCE: The Gini and occupation HHI are calculated using the ACS. The curriculum HHI is calculated from the restricted-use Baccalaurate and Beyond data.

5 Estimating the Returns to Specialized Majors

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 bachelor's degree holders for their undergraduate 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.

5.2 Estimation

We explore several outcomes, including annual wage and salary income (top-coded at \$500,000), hours worked, hourly wages, employment, and the probability of being a manager or entrepreneur. We estimate regressions of the form:

$$y_i = \beta_0 + \beta_1 \mathrm{exp} + \beta_2 \mathrm{exp}^2 + \beta_3 \mathrm{spec}_i + \beta_4 \mathrm{spec}_i * \mathrm{exp} + \beta_5 \mathrm{spec}_i * \mathrm{exp}^2 + \Gamma_1 X_i + \Gamma_2 M_i + \mathrm{year}_i \quad (5)$$

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 (average SAT math and verbal scores and the variance of SAT scores within the major). Potential experience is the current year minus the inferred graduation yaer, based on the respondent's birth date. The major characteristics are included to control for average ability in the major as well as we can. We also include year fixed effects to control for changing economic conditions.[18]

In our data, some majors have far more observations than others.[19] 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 each of our majors.

We cannot interpret the results below as the causal effects of majoring in specific fields. While we do control for average SAT scores by major, there could be unobservable factors that also vary across majors. We will provide evidence that our results are robust to different approaches and subsamples, but we cannot claim causality. Still, the results are of descriptive interest and at least suggestive of possible causal effects.

[18] 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.

[19] 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.

5.3 Earnings Returns

We start with annual wage and salary earnings. Table 4 shows that more specific majors (higher Gini) have an overall earnings return per standard deviation of about 2%. The initial return (column 2) is 7-8% per standard deviation, which fades slowly with age.

Table 4: **Earnings Return to Specificity (Coefficients Multipled by 100)**

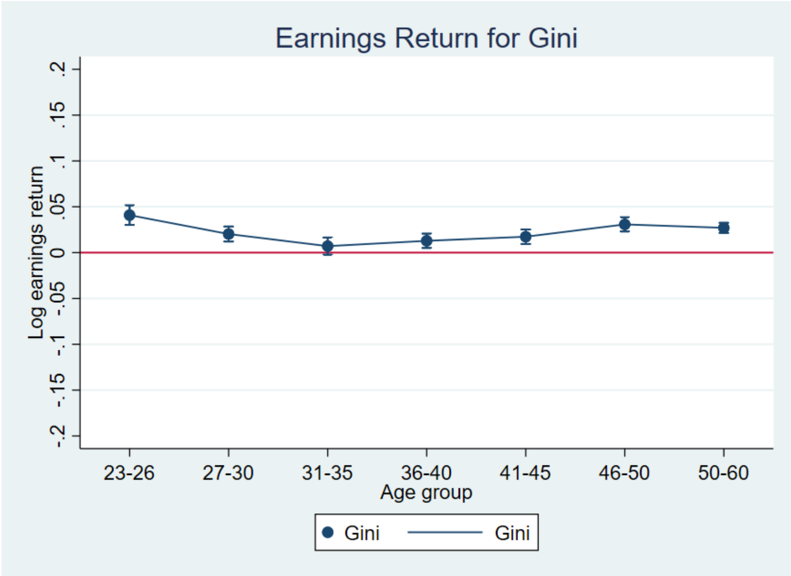
	Dependent variable: log annual earnings							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	1.980***	7.250***						
	(0.115)	(0.347)						
Gini*potexp		-0.565***						
		(0.038)						
Gini*potexp^2		0.012***						
		(0.000)						
Vocational			-0.810***	18.090***				
			(0.237)	(0.648)				
Vocational*potexp				-1.890***				
				(0.075)				
Vocational*potexp^2				0.037***				
				(0.002)				
Occ HHI					1.522***	7.685***		
					(0.068)	(0.196)		
Occ HHI*potexp						-0.724***		
						(0.022)		
Occ HHI*potexp^2						0.016***		
						(0.000)		
Curric. HHI							-0.393***	-0.415
							(0.112)	(0.332)
Curric. HHI*potexp								-0.144***
								(0.040)
Curric HHI*potexp^2								0.006***
								(0.001)
Constant	30.329***	30.560***	28.847***	28.775***	29.755***	29.936***	28.827***	28.574***
	(0.951)	(0.950)	(0.929)	(0.928)	(0.939)	(0.939)	(0.933)	(0.935)
Observations	2,598,334							
R-squared								

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
NOTE: 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. The sample is restricted to college graduates aged 23 to 60. We have multiplied the coefficients and standard errors in the table by 100 to more clearly show how effects change with age.
SOURCE: The Gini and occupation HHI are calculated using the ACS. The curriculum HHI is calculated from the restricted-use Baccalaurate and Beyond data. The sample is from the ACS 2009-2015.

To get a better sense of how the returns change with age, Figure 3 shows estimates of the return to one standard deviation of the Gini measure,[20] estimated using separate regressions by age group. There is a positive return to more specific majors

[20]To give some context, the journalism major has an average Gini, finance is about one standard deviation above the mean, and psychology is about one standard deviation below the mean.

Figure 3: **Earnings Return: 1 Standard Deviation of Gini**



SOURCE: Authors' calculations from regressions using the ACS 2009-2015.

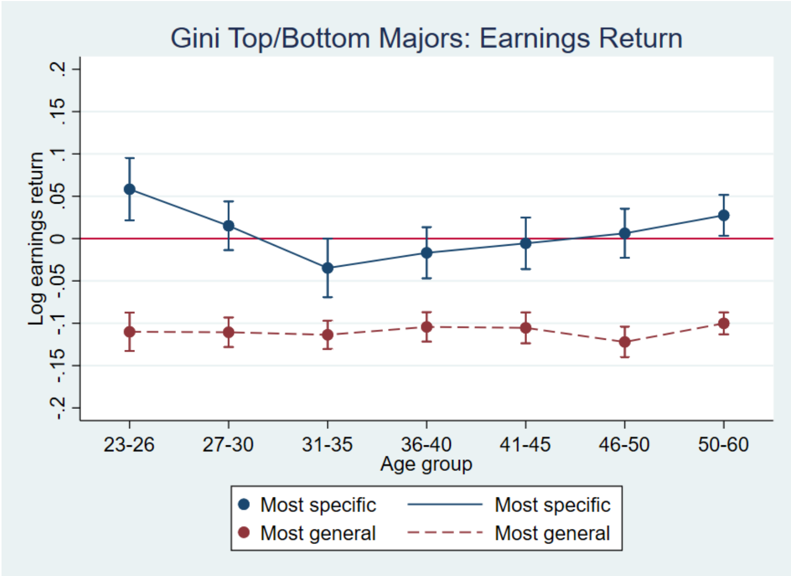
at every age level, which is significant for all but age 31-35. The initial advantage here is about 5%, and it remains between 0% and 5% for the whole life cycle.

These regressions include only major-average SAT scores, which may not allay concerns about selection into majors on ability. We can estimate the return to specificity with a smaller sample and fewer majors using the Baccalaureate and Beyond 08/12 data, in which we include individual SAT math and verbal scores. Using these data, the return to one standard deviation of Gini for workers four years out of college is 10%, even larger than in our ACS estimates for young workers. This suggests that our results are not driven by selection on observable factors into more specific majors.[21]

Figure 4 shows age-specific earnings estimates for the top ten and bottom ten most specific majors according to the Gini measure. The most specific majors earn an initial premium of about 6% over average majors. This declines with age, and is slightly negative in the 30s, but turns positive again at later ages. On the other hand, general majors fare far worse than average and specific majors, earning about

[21]The results from the B&B data are available upon request.

Figure 4: **Earnings Return: Gini**



SOURCE: Authors' calculations from regressions using the ACS 2009-2015.

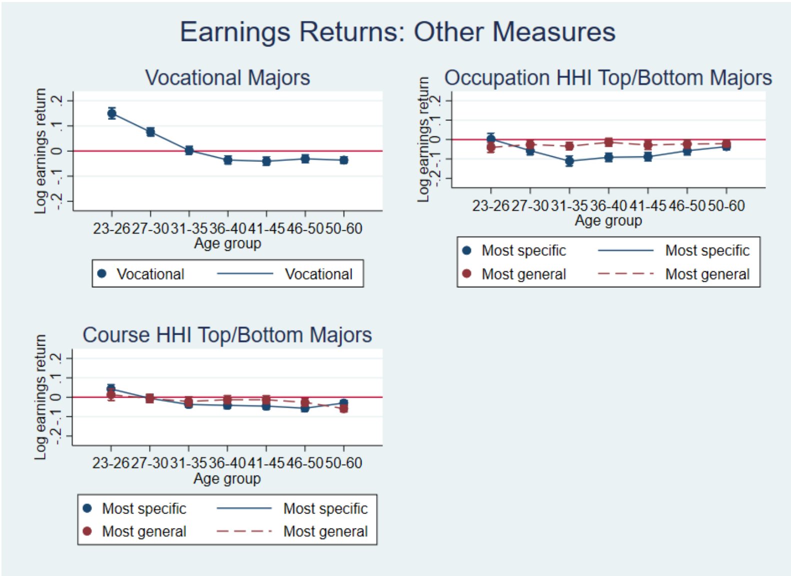
10% below average at all ages, and over 15% less than specific majors early in the career.[22]

We can compare these results to those using the other three measures, shown in Figure 5. The vocational measure 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. Despite "vocational" meaning something different here than in a European context, this finding is consistent with some of the literature on returns to vocational education (e.g., Hanushek et al. (2017), Golsteyn and Stenberg (2017)). On the other hand, Silliman and Virtanen (2019) find that vocational training in Finland has a lasting positive return.

The occupation HHI and curriculum HHI show a less optimistic picture for specific

[22]Our results are broadly similar to those in Deming and Noray (2018), who find that STEM degrees have a high early-career premium that declines with age. Most STEM majors are specific according to our Gini measure, though some are not, and many non-STEM majors are also specific, so our results are difficult to compare to theirs.

Figure 5: **Earnings Return: Other Measures**



SOURCE: Authors' calculations from regressions using the ACS 2009-2015.

majors. At most ages, the return to specific majors is negative, especially for the occupation HHI. The difference between our Gini returns and the occupation HHI returns is surprising, given that the two measures are positively correlated. This tells us that the Gini is picking up something different from the occupation HHI.

Thus, our results from the Gini are quite different from existing measures. We find that specificity has a positive return at almost every age, and the most general majors always have the lowest return.[23] The Gini measure is also powerful in "explaining" earnings variance across majors. Dominance Analysis (Budescu (1993)) shows that our Gini measure explains more of the variance in earnings across majors than any of the other specificity measures.[24]

We have performed our analysis several other ways, with results available in Appendix B. When graduate degree holders are excluded, the results for the Gini measure are nearly identical (Figure B.1). We have also used the top and bottom five

[23]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 and better citizens, and may lead to more interesting jobs. These outcomes are more difficult to quantify.

[24]These results are available on request.

majors and the top and bottom third of majors (Figure B.2). The conclusions are again similar. Specific majors earn slightly more than average at most ages, while general majors are always below average. We have also split the sample in two based on average SAT scores in Figure B.3. The return to specific majors is concentrated among the higher-SAT majors.

Finally, Figure B.4 shows the estimated earnings return for the most specific and most general majors at the 20th and 80th percentiles of the earnings distribution. While estimates are imprecise, they show that early in life, specific majors do well at both parts of the distribution. Later in life, the return to specific majors is being driven by the 20th percentile. Meanwhile, the most general majors are the lowest-earning in both cases.

5.4 Decomposing the Earnings Effects

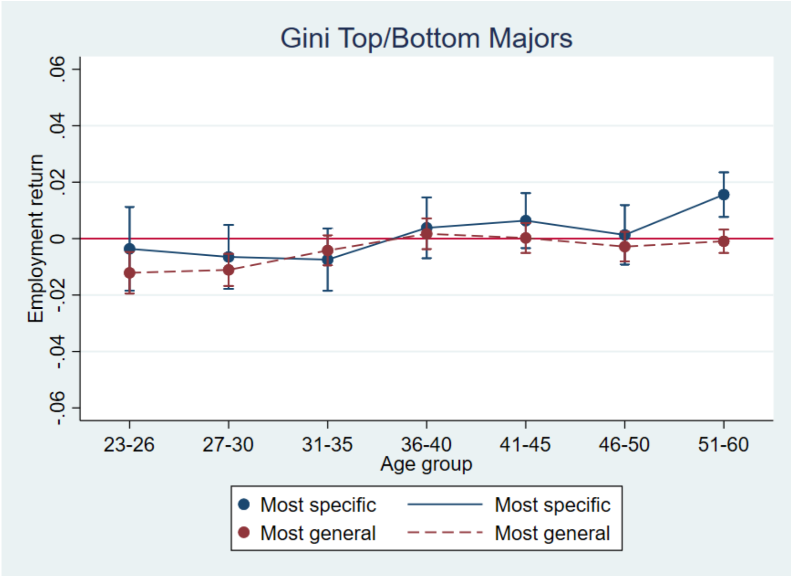
We have seen a generally positive earnings return to more specific majors. Now we decompose this by looking at hours worked, hourly wages, and the probability of employment. These exercises are important because higher earnings could come through a higher probability of working (or working full-time) or through higher earning power per hour. When students evaluate majors, they may be thinking about the security of getting a job, for example. Even if specific majors earn more on average, it could be that there is a risk of not getting a job at all.[25]

Figure 6 shows the employment probability return to the most general and most specific majors.[26] These are probit regressions, and we graph the marginal effects; linear probability models give a similar result. There is little employment difference between specific and average majors, but general majors have an initial employment disadvantage to match their earnings disadvantage. Specific majors have a slight advantage later in life.

[25] Tables of regression results for employment, hours, and wages are available in Appendix C.

[26] 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.

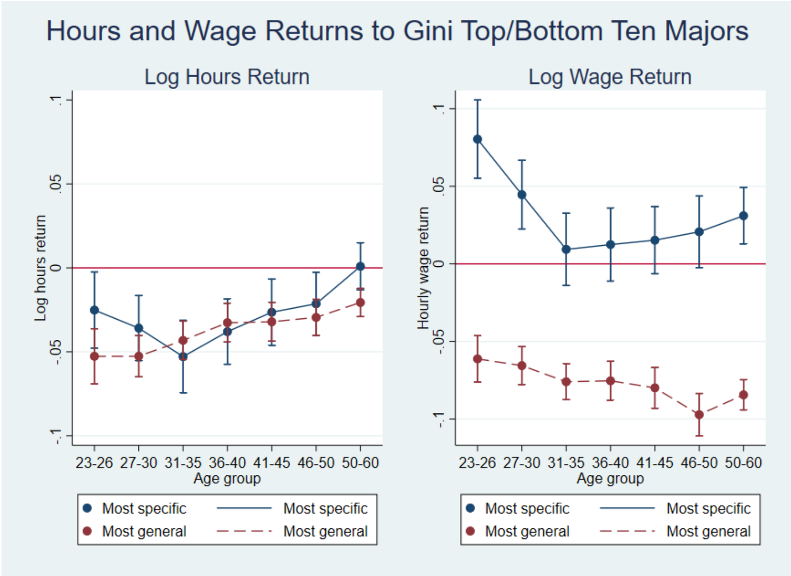
Figure 6: **Employment Return: Gini**



SOURCE: Authors' calculations from regressions using the ACS 2009-2015.

Figure 7 breaks the earnings return down into log hours and log hourly wages. The results are striking. Specific majors have a large wage premium over average majors (about 8%) and a small hours penalty. All of their earnings advantage is coming through wages. General majors face an especially large penalty in wages. The hourly wage advantage for the most specific majors over the most general is about 15%.

Figure 7: **Hours and Wage Returns: Gini**



SOURCE: Authors' calculations from regressions using the ACS 2009-2015.

5.5 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, finding that those who took a more balanced MBA curriculum, and those who had held more different jobs before going to business school, were more likely to become entrepreneurs.[27]

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

[27] Other research has shown similar findings, primarily focusing on the prior job roles held by those who become entrepreneurs (e.g., Wagner (2006)).

education beyond entrepreneurs, to those holding managerial roles – regardless of whether those roles are in self-employment or not.

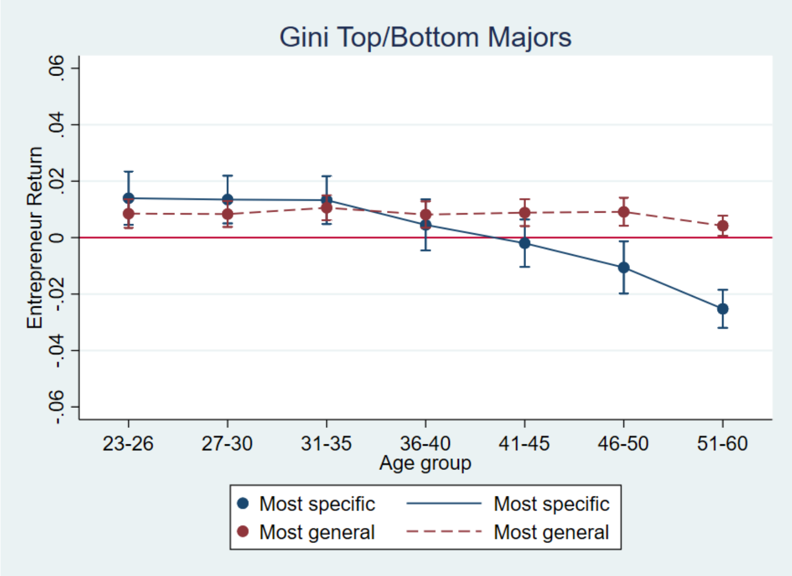
We use our Gini measure of specificity to explore the hypothesis that general education is associated with a higher probability of being an entrepreneur, or of holding a managerial occupation. Because our data do not allow us to definitively identify true entrepreneurs, we use business income as a proxy 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. About 16% of our observations are managers, while about 9% are entrepreneurs.

Figure 8 repeats our primary analysis, with the dependent variable now a binary indicator for being an entrepreneur.[28] We do find that general majors are more likely than average majors to become entrepreneurs, but so are specific majors (at least early in life). Later in life, general majors are most likely to be entrepreneurs, as the theory would predict. Our Gini measure may not be picking up some of the general skills that predict entrepreneurship (e.g., people skills).[29]

[28]Figures 8 and 9 are results from probit regressions, and we graph the marginal effects. 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.5 and B.6. 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.

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

Figure 8: **Entrepreneurship and specificity**



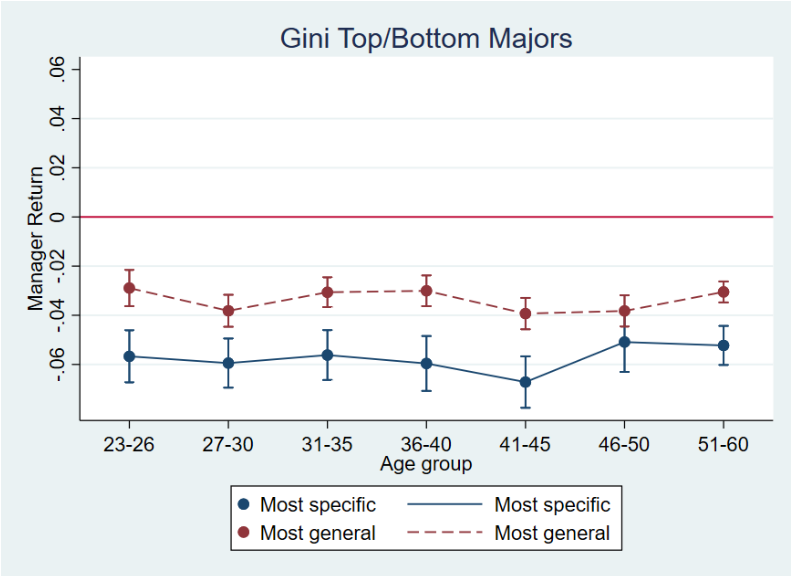
SOURCE: Authors' calculations from regressions using the ACS 2009-2015.

Figure 9 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 -0.06 implies about a 40% reduction in the likelihood of being a manager, which is persistent throughout the career. Surprisingly, general majors are also less likely than average majors to become managers. This could be because while managers use a variety of skills, they also need expertise in the specific field they are managing, and thus average majors, which are not too specific nor too general, have the highest rates of management.

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. (2016)). 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

Figure 9: **Managers and specificity**



SOURCE: Authors' calculations from regressions using the ACS 2009-2015.

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.

Our primary contribution 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 approach, education and nursing are the most specific majors, while music, philosophy, and psychology are among the most general. We find that specific majors' graduates earn the most at almost every age. The initial premium is about 5% over average majors and 15-20% over general majors, driven entirely by higher wages. In contrast with most results on vocational education, there is little tradeoff between early- and late-career success. The most general majors always earn far less than average or specific majors.

While there is a high return to specialized skills, those from specific fields are actually the least likely to be managers. Majors of average specificity – neither very general nor very specific – are most likely to hold these positions. Managers may require a mix of general skills and specific expertise.

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.

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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.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.[30] 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.3 shows the majors we count as vocational or academic, based on the taxonomy from the National Center for Education Statistics.

A.2 Notes on Aggregation of Majors and Occupations

Using 51 majors and 11 occupations, our data has full support. The smallest major-occupation cell in our ACS sample includes 6 individuals (Computer Programming graduates working in the Research, Scientists, Technical occupation), while the largest includes 44,242 (Primary/General Education graduates working as Educators). The mean cell size is 1,631 and the median is 629.

Perhaps unsurprisingly, our measure is sensitive to the level of aggregation of both majors and occupations. When more aggregated major categories are used, general

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

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

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

SOURCE: The Gini and occupation HHI are calculated using the ACS. The vocational categorization is adapted from the NCES postsecondary taxonomy. The curriculum HHI is calculated from the restricted-use Baccalaurate and Beyond data.

and specific majors are often lumped together. We have tried several alternative classifications of majors and occupations. To avoid empty cells, we cannot increase the number of majors or occupations, but can aggregate to fewer majors (e.g., 14) and occupations (e.g., 5). In both cases, the correlation between the new measures and our baseline measure is around 0.5. We have also calculated our Gini using 14 industries instead of occupations, which maintains full support. The correlation between this and our baseline measure is 0.59. When thinking about the transferability of human capital, we feel that occupations are more appropriate to use than industries (see, e.g., Kambourov and Manovskii (2009)).

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 (Dropped)	45	Farming, Fishing, and Forestry Occupations
	55	Military Specific Occupations

SOURCE: Occupation categories are taken from the Baccalaureate and Beyond data. The SOC codes are from the Bureau of Labor Statistics.

Table A.3: **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: Adapted from the NCES Postsecondary Taxonomy.

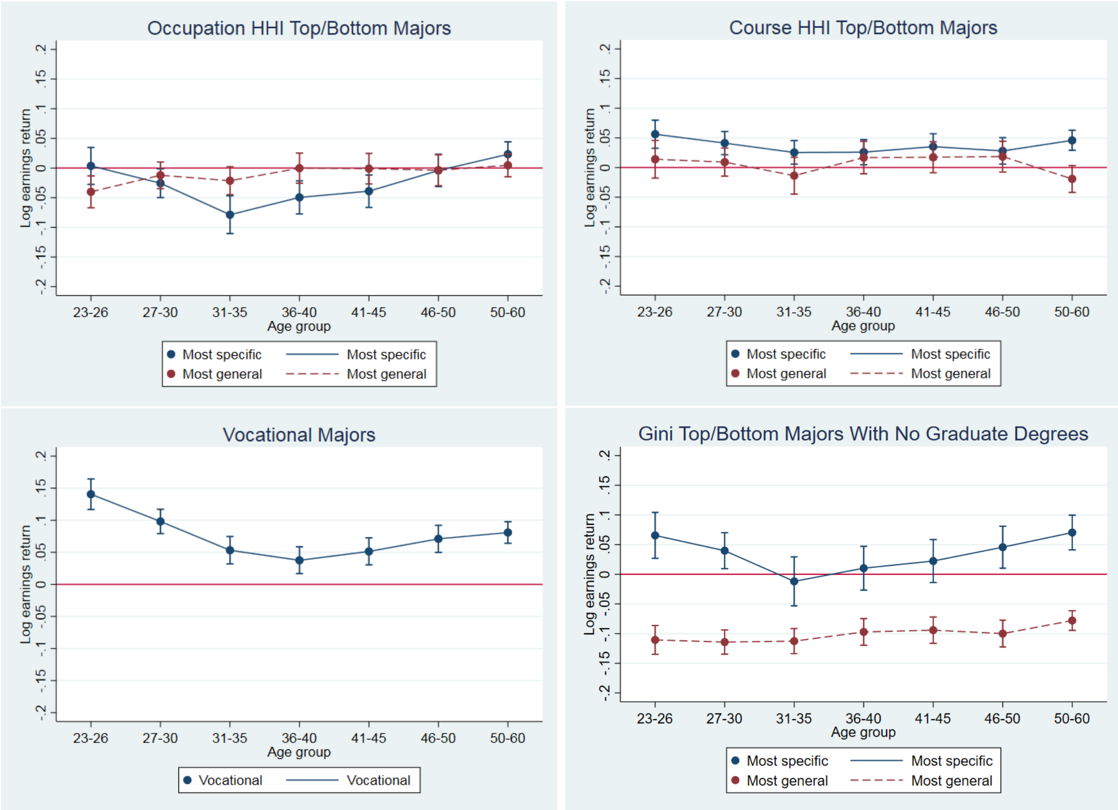
B Appendix Figures

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.2 replicates 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 4) 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) or top and bottom 17 (thirds).

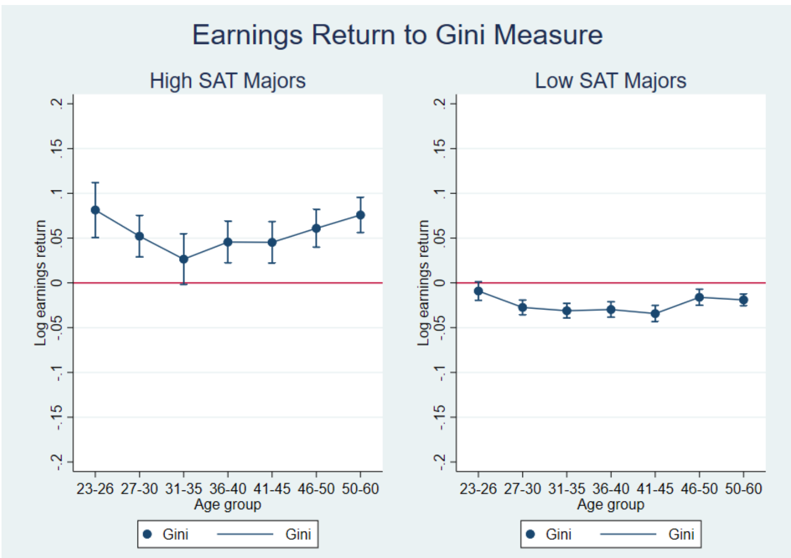
Figure B.3 splits the sample into majors that have above-average average SAT scores and those that are below average. The results show that the return to specificity is concentrated among the high-SAT majors.

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



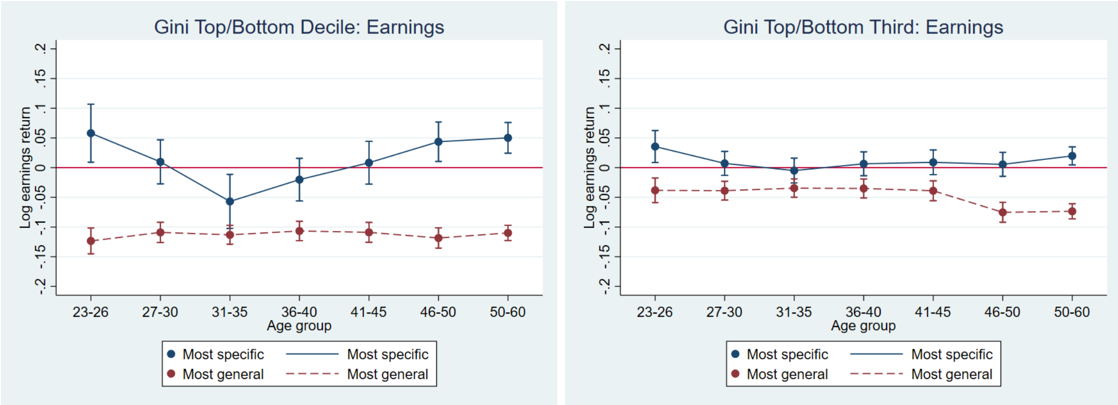
SOURCE: Authors' calculations from regressions using the ACS 2009-2015. The occupation HHI and Gini are calculated using the ACS, and the curriculum HHI is calculated using the restricted-use Baccalaureate and Beyond data. The vocational categorization is taken from the NCES postsecondary taxonomy.

Figure B.3: **High vs. Low SAT Majors**



SOURCE: Authors' calculations from regressions using the ACS 2009-2015. Average SAT scores by major are taken from the restricted-use Baccalaureate and Beyond data.

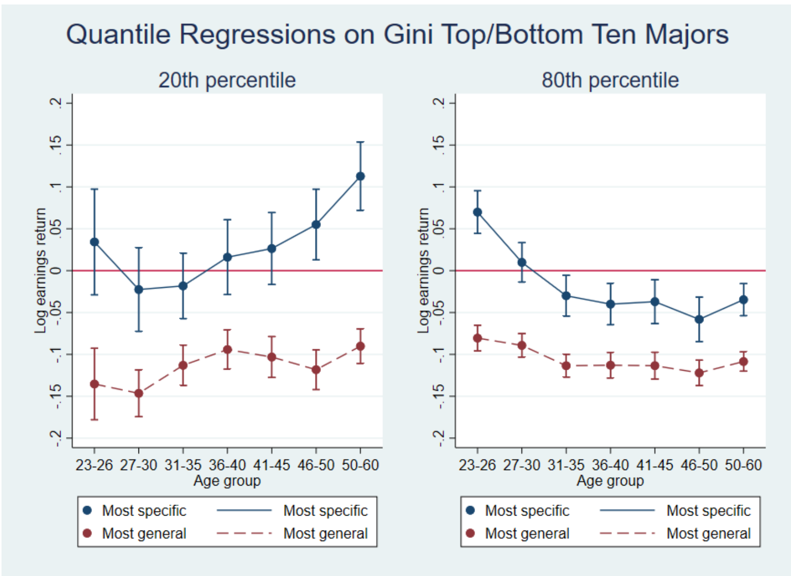
Figure B.2: **Earnings Return: Deciles & Thirds**



SOURCE: Authors' calculations from regressions using the ACS 2009-2015.

Figure B.4 shows the estimated earnings return for the most specific and most general majors at the 20th and 80th percentiles of the earnings distribution. Early in life, specific majors do well at both parts of the distribution. Later in life, the return to specific majors is being driven by the 20th percentile. The most general majors are the lowest-earning in both cases.

Figure B.4: **Quantile Earnings Return: Gini**



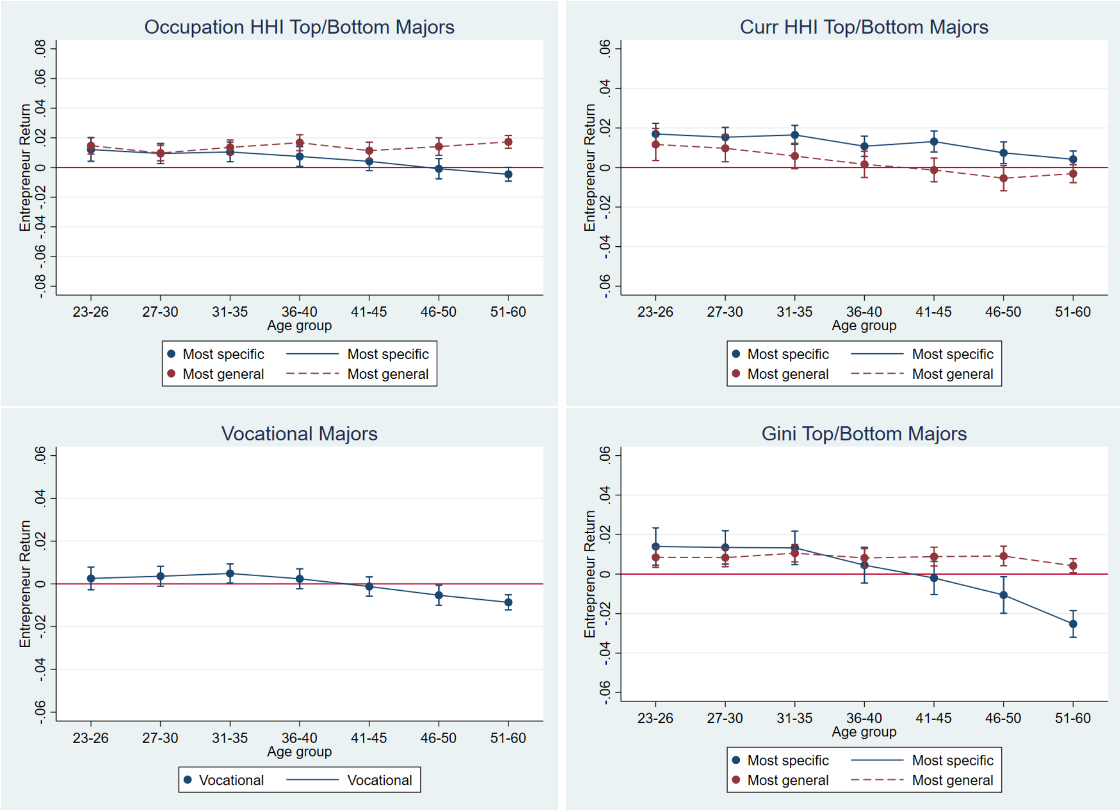
SOURCE: Authors' calculations from regressions using the ACS 2009-2015.

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.5 and B.6 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.5: **Entrepreneurship and Specificity - All Measures**



SOURCE: Authors' calculations from regressions using the ACS 2009-2015. The occupation HHI and Gini are calculated using the ACS, and the curriculum HHI is calculated using the restricted-use Baccalaureate and Beyond data. The vocational categorization is taken from the NCES postsecondary taxonomy.

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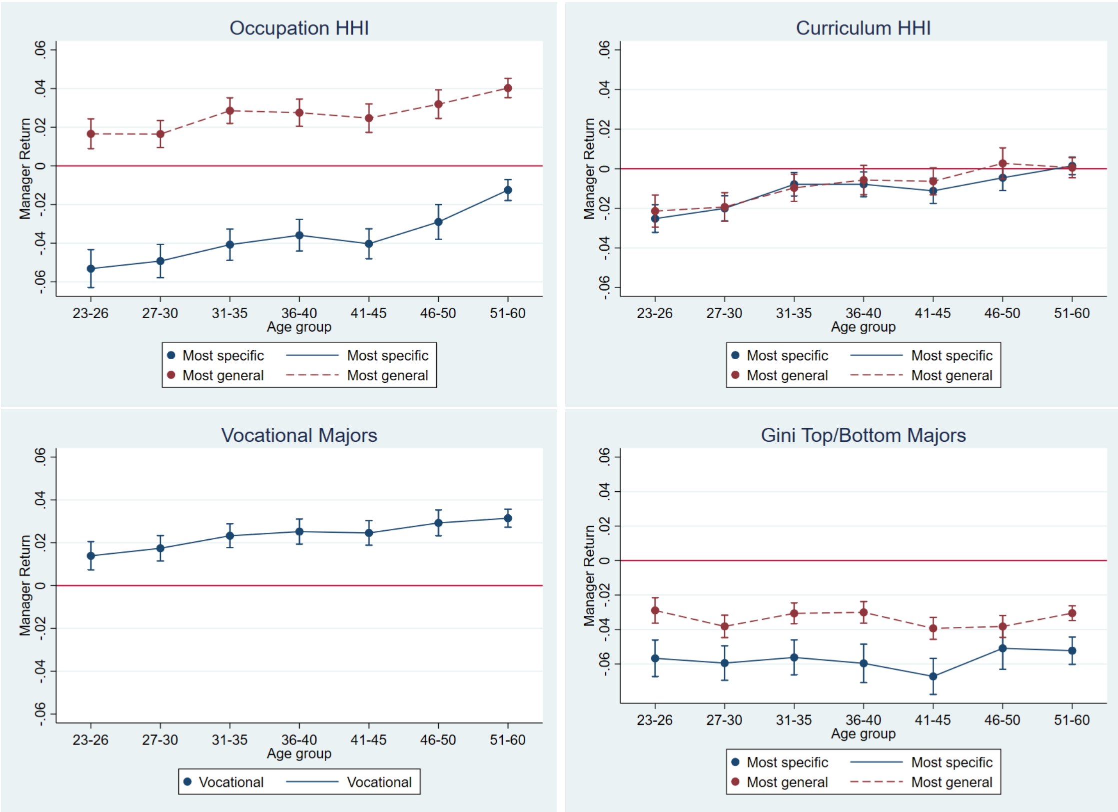
Figure B.6: **Management and Specificity - All Measures**



SOURCE: Authors' calculations from regressions using the ACS 2009-2015. The occupation HHI and Gini are calculated using the ACS, and the curriculum HHI is calculated using the restricted-use Baccalaureate and Beyond data. The vocational categorization is taken from the NCES postsecondary taxonomy.

Table C.1: **Log hours (Coefficients multipled by 100)**

	(1) log hours	(2) log hours	(3) log hours	(4) log hours	(5) log hours	(6) log hours	(7) log hours	log hours
Gini	0.369*** (0.072)	1.012*** (0.216)						
Gini*potexp		-0.083*** (0.024)						
Gini*potexp^2		0.002*** (0.000)						
Vocational			1.363*** (0.148)	5.229*** (0.431)				
Vocational*potexp				-0.438*** (0.049)				
Vocational*potexp^2				0.010*** (0.001)				
Occ HHI					-0.137*** (0.045)	0.223* (0.134)		
Occ HHI*potexp						-0.099*** (0.015)		
Occ HHI*potexp^2						0.003*** (0.000)		
Curric. HHI							-0.763*** (0.071)	-0.637*** (0.219)
Curric. HHI*potexp								-0.058** (0.026)
Curric. HHI*potexp^2								0.002*** (0.000)
Constant	11.900*** (0.599)	11.924*** (0.599)	11.387*** (0.586)	11.396*** (0.587)	11.508*** (0.592)	11.503*** (0.592)	11.811*** (0.589)	11.741*** (0.590)
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	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
NOTE: 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.
SOURCE: The Gini and occupation HHI are calculated using the ACS. The curriculum HHI is calculated from the restricted-use Baccalaurate and Beyond data. The sample is from the ACS 2009-2015.

Table C.2: **Log Wages (Coefficients multiplied by 100)**

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage	(6) log wage	(7) log wage	log wage
Gini	1.855***	6.212***						
	(0.085)	(0.249)						
Gini*potexp		-0.473***						
		(0.028)						
Gini*potexp^2		0.010***						
		(0.000)						
Vocational			-1.921***	12.667***				
			(0.178)	(0.453)				
Vocational*potexp				-1.419***				
				(0.054)				
Vocational*potexp^2				0.027***				
				(0.001)				
Occ HHI					1.778***	7.424***		
					(0.049)	(0.136)		
Occ HHI*potexp						-0.623***		
						(0.016)		
Occ HHI*potexp^2						0.013***		
						(0.000)		
Curric. HHI							0.157*	0.249
							(0.083)	(0.235)
Curric. HHI*potexp								-0.102***
								(0.029)
Curric. HHI*potexp^2								0.004***
								(0.000)
Constant	18.799***	18.988***	17.589***	17.512***	18.497***	18.674***	17.245***	17.096***
	(0.713)	(0.713)	(0.696)	(0.696)	(0.705)	(0.705)	(0.699)	(0.700)
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	0.136	0.136	0.136	0.137	0.136	0.136	0.136	0.136

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
NOTE: 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.
SOURCE: The Gini and occupation HHI are calculated using the ACS. The curriculum HHI is calculated from the restricted-use Baccalaurate and Beyond data. The sample is from the ACS 2009-2015.

Table C.3: **Employment (Probit; Coefficients multiplied by 100)**

	(1) employed	(2) employed	(3) employed	(4) employed	(5) employed	(6) employed	(7) employed	employed
Gini	2.743***	-0.464						
	(0.185)	(0.660)						
Gini*potexp		0.360***						
		(0.067)						
Gini*potexp^2		-0.008***						
		(0.001)						
Vocational			5.075***	4.429***				
			(0.383)	(1.14)				
Vocational*potexp				0.174				
				(0.122)				
Vocational*potexp^2				-0.005*				
				(0.003)				
Occ HHI					3.534***	0.985***		
					(0.107)	(0.336)		
Occ HHI*potexp						0.225***		
						(0.035)		
Occ HHI*potexp^2						-0.004***		
						(0.000)		
Curric. HHI							2.169***	4.018***
							(0.178)	(0.634)
Curric. HHI*potexp								-0.259***
								(0.070)
Curric. HHI*potexp^2								0.006***
								(0.002)
Constant	2.785*	2.679*	0.388	0.360	3.318**	3.25**	0.838	0.843
	(1.578)	(1.578)	(1.540)	(1.541)	(1.556)	(1.556)	(1.538)	(1.538)
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
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
NOTE: 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.
SOURCE: The Gini and occupation HHI are calculated using the ACS. The curriculum HHI is calculated from the restricted-use Baccalaurate and Beyond data. The sample is from the ACS 2009-2015.