Racial and Gender Differences in School-College-Career Paths*

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Abstract

This paper examines the factors affecting early career gender and racial wage gaps. Using a rich longitudinal administrative data from Minnesota and a dynamic discrete choice model, we evaluate role of various channels that potentially affect these wage gaps: *endowments* of school quality, family background, and ability; the *decision path* of sequential human capital investment made by individuals in high school, college, and labor market; and a *returns to skill* component, estimated given endowments and decision path. The initial gender wage gap is driven almost entirely by differential returns to the same skills, not by differences in endowments or in the school-college decision paths. For racial gaps, all three channels contribute to the early wage gaps, with the biggest contribution coming from differences in endowments. Our results show that education policies that encourage individuals to take STEM paths would have little effect on reducing either gender or racial wage gap. Education interventions in schools before individuals reach high school can be most effective in reducing early career White-Black wage gap.

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1 Introduction

Despite decades of progress, gender and racial disparities in wages still exist in the United States: females earn less than males and Black and Hispanic workers earn less than White workers. At the same time, there is increasing evidence that differences in learning ability and initial conditions in the labor market account for more of the variation in lifetime earnings compared to differences in shocks received over the working lifetime of an individual (Huggett et al. (2006), Huggett et al. (2011)).

This paper examines the importance of human capital investments in high school and college for explaining early career wage differences and opens the black box of what goes into these initial labor market conditions. We focus our analysis on early career outcomes of individuals for two reasons. First, the wage gaps across demographic groups increase, not close, over workers' life cycle (Goldin et al. (2017), Rauh and Valladares-Esteban (2018)). It is therefore important to understand why there is an initial gap. Second, factors affecting wage gaps later in life, such as differences in home responsibilities (Goldin (2014), Blau and Kahn (2017), Erosa et al. (2022)), promotion standards (Lazear and Rosen (1990)), or wage bargaining abilities (Babcock and Laschever (2003)), are not likely to affect wage differences in the first jobs. Policy responses to factors that affect initial wage gaps would therefore be likely different from policy responses that explain gaps over the working life cycle.

We use a novel data set from the state of Minnesota which contains information on students from kindergarten through post secondary education into the work force. A unique feature of the labor market information in our administrative dataset is that for each worker, we observe quarterly hours worked in addition to quarterly earnings. This allows us to construct hourly wages, hence removing the differences in hours worked as a source of inequality. Our main outcome of interest is average hourly wages of individuals in the first three years of the labor market after their terminal degree.

We use information on students before they enter high school to measure differences in their endowments or initial states. We use standardized test scores and attendance to construct measures of cognitive and non-cognitive ability measures respectively. We use enrollment into free or reduced price lunch as a proxy for socioeconomic background and language spoken at home as a proxy for cultural factors. We also control for the quality of high school students attend. We use a Value Added Model to obtain the distribution of school quality and Empirical Bayes Methods to improve the estimates for each school.

Given the initial endowments, we examine how individuals make sequential decisions in high school, college, and the labor market. The first choice individuals make is what type of advanced courses they enroll into in high school. In order to ensure that the enrollment differences are driven

by choices and not due to availability of advanced courses, we restrict our analysis to schools which offer them (most public schools in Minnesota offer such courses).

At the end of high school, students decide whether to attend college or not. Students who go to college can choose between a two-year college or a four year college. Those who choose a two-year college are designated as choosing "some college." If an individual chooses to go to a four year college, we define four categories based on the quality of college and the major chosen: STEM major in high quality college, STEM major in low quality college, Non-STEM major in high quality college, and Non-STEM major in low quality college. Students who enroll in a four-year college but drop out are put in the same category as those going to a two-year college, i.e."some college." Students who did not go to college do not make any choices at this point in the sequence. They go directly to the labor market. Once in the labor market, the individuals choose one of nine industries to work in.

We refer to this sequence of choices made at different stages in life as the school-college-career decision path (or simply the path). We use a dynamic discrete choice model to analyze the decisions that students make on each node of the path.

We model students as forward-looking agents who make a sequence of discrete choices over high school courses, college majors, and labor market industries. Students enter the model with an observable state vector capturing cognitive and non-cognitive ability, socioeconomic status, cultural background, and high school quality, along with a latent preference type that governs the non-pecuniary utility they derive from different educational paths and the weight they place on expected future earnings. At each node, students choose among alternatives by trading off these non-pecuniary preferences against the continuation value of future choices. The model thus captures not only the direct effect of early decisions on earnings, but also how choices at one stage shape the feasible set and incentives at subsequent stages.

Unobserved heterogeneity enters the model through two distinct channels. The first is a latent preference type, shared across the high school and college nodes, which captures heterogeneity in students' intrinsic tastes for different fields of study and in how forward-looking their educational choices are. The second is a labor market productivity type, determined by observable characteristics and the school-college path, which governs earnings levels and subsequent wage growth. The two-type structure allows the model to separately identify why individuals sort into different educational paths from why the same path translates into different labor market outcomes across demographic groups.

We estimate the model in stages, working backwards from the labor market. In the first stage, we use an AKM regression to estimate worker fixed effects and assign workers to four labor market productivity types based on their position in the fixed effect distribution. For each type and demographic group, we estimate a wage equation relating log earnings to observable characteris-

tics, school-college path choices, and industry. We then recover the present discounted value of earnings using age-wage profiles estimated on earlier cohorts, and the systematic industry amenities and scale of idiosyncratic amenity shocks using observed industry shares. In the final stage, we jointly estimate the parameters governing high school and college choices using an EM algorithm that exploits the Arcidiacono and Miller (2011) conditional choice probability approach. The latent preference type is shared across both nodes, so the E-step uses information from both the high school and college choices jointly to update posterior type probabilities, while the M-step updates the preference parameters separately for each node.

The distribution of productivity types is very similar for men and women, but markedly different for White and Black workers, with Black workers disproportionately concentrated in the lowest-productivity types. We estimate the production function of labor market productivity types using multinomial logit and report the average marginal effect of observable characteristics and path choices on the probability of being assigned to a certain type. We find that cognitive ability is a strong predictor of entry into the highest productivity types, with school quality, socioeconomic disadvantage, and learning trajectories also playing meaningful roles. College path is especially consequential: STEM degrees and attendance at higher-quality colleges substantially increase the likelihood of reaching the top labor-market types, although the same educational choices translate into larger productivity gains for men than for women. By contrast, racial differences in within-type wages are comparatively small, suggesting that unequal sorting across productivity types is a central part of the White-Black wage gap.

The wage regressions further show that direct returns to high-school course taking are modest, consistent with the view that the primary value of AP and CTE courses operates indirectly through their effect on college choices and labor market productivity type. College choices —especially STEM fields and college quality— generate large wage premia. The college premium is generally larger for women than for men across all college paths and most productivity types. This is partially offset by the fact that women are less likely to be assigned to the high-productivity types conditional on the same college path, and the baseline wage constants are lower for women within each type. Black workers in the highest type receive larger returns to STEM degrees than White workers while the low-productivity Black workers benefit little from college credentials in terms of wages. The estimated age-wage profiles also fan out by productivity type, implying that early differences in productivity matter not only for starting wages but also for subsequent earnings growth.

Our estimation results also show that substantial heterogeneity in preferences governs course and major choices before labor-market entry. The model identifies three latent preference types that differ in how forward-looking students are and in how responsive they are to expected earnings. In the gender specification, men are more likely to belong to the highly earnings-responsive type,

whereas women are more concentrated in a type with stronger but more diffuse course preferences. In the race specification, forward-looking behavior in early schooling decisions is weaker overall, and Black students are more likely to be assigned to a type whose choices are dominated by non-pecuniary tastes.

Taken together, these estimation results show that the model fits observed school and college choices well while also clarifying how initial conditions, educational decisions, and labor-market sorting interact to generate early-career wage differences.

We then use the estimated model to move from interpretation to counterfactual analysis. We first decompose the initial wage gap into five channels—observable initial conditions, latent preference types, labor-market productivity types, returns to skills, and realized school-college-career path choices—and then evaluate two classes of policy interventions: broad encouragement of STEM at different stages of the pipeline and a targeted improvement in school quality for students in the lowest-quality schools. In doing so, we clarify not only where early-career wage gaps come from, but also which interventions are likely to reduce them and which may unintentionally widen them.

The central finding is that the mechanisms behind gender and racial wage inequality are fundamentally different. For gender, the model implies a modest initial wage gap that disappears—and slightly reverses—once women are given the same returns to skills as men, indicating that the gap is driven primarily by lower returns rather than by weaker endowments or worse educational choices. Indeed, several equalization exercises make the gender gap larger, implying that women's observed characteristics and path choices already partially offset the disadvantage they face in the labor market. For the White-Black gap, by contrast, the dominant force is unequal pre-labor-market conditions: equalizing observable initial characteristics cuts the gap by more than half, while equalizing path choices has almost no effect. Racial wage inequality therefore appears to be rooted mainly in differences in early endowments and subsequent sorting, with differential returns playing a secondary but still meaningful role.

The policy counterfactuals reinforce this asymmetry. Universal STEM encouragement has almost no effect when applied at the high-school course stage, and although subsidizing STEM majors in college does increase STEM enrollment and wages, it benefits men and White students more than women and Black students, slightly widening both gaps. By contrast, improving school quality for students in the lowest-quality schools raises wages for all groups, with substantially larger gains for Black students than for White students, thereby modestly narrowing the racial gap while leaving the gender gap largely unchanged.

We conclude that interventions aimed at changing later educational choices are unlikely to eliminate early-career inequality on their own: gender disparities primarily reflect differences in returns, whereas racial disparities are more deeply tied to inequalities in school quality, ability, and

family background.

Relation to the literature. Our paper contributes to a rich literature on gender and racial wage gaps. In explaining gender wage gaps over the lifecycle, recent studies have documented that human-capital factors are relatively unimportant (Altonji and Blank (1999), Goldin (2014), Blau and Kahn (2017)) and that gender-specific value of job flexibility, differential occupational choice, and differential hours worked are more important factors. Our paper focuses on early careers rather than wage gaps over the life cycle and shows that the sequence of choices made along the school-college-career paths are important factors for explaining wage gaps in initial jobs. Since gender wage gaps increase over the life cycle (Goldin et al. (2017)), our results suggest that human-capital factors should not be ignored.

While the importance of pre-labor-market factors in White-Black wage gaps and labor market outcomes has been documented in the economics literature (Altonji and Blank (1999), Cameron and Heckman (2001), Carneiro et al. (2005), Fryer (2011)), there is a debate about the relative importance of various pre-labor market factors. In 1987, years of schooling completed and scores on the Armed Forces Qualifications Test (AFQT) accounted for 75% of the hourly earnings difference between Whites and Blacks, and differences in work experience accounted for most of the remaining gap (O'Neill (1990)). The remaining White-Black wage differential among young men was around 7%, and statistically insignificant (Neal and Johnson (1996)). Black et al. (2006) argue that the AFQT is a better measure of pre-market human capital than years of schooling. They additionally control for non-test college degree-level characteristics, such as field of highest degree. They find that after controlling for these characteristics, no racial differences in wages emerges.

In subsequent studies, the wage differential between black and white men was found to be larger than Neal and Johnson (1996) estimate (Carneiro et al. (2005), Rodgers III and Spriggs (1996)). Upon controlling for years of schooling at the time the AFQT test was taken, a larger wage differential emerges (Lang and Manove (2011)). Lang and Manove reject the hypothesis that this is due to differences in school quality between blacks and whites. Instead, they argue that the wage gap is likely due to differential treatment in the labor market, such as statistical discrimination in the search process.

Our paper sheds light on the debate by bringing a rich longitudinal administrative data that allows us to examine these various factors in early careers of individuals. Our results suggest that while both these factors are at play, within-path component is significantly larger than the across-path components in explaining racial wage gaps. In other words, our results are closer to the findings of Lang and Manove (2011).

We also contribute to the literature which examines the impact of high school curriculum on the choice of major and earnings. Joensen and Nielsen (2009) exploit educational reform in Denmark

in 1988 that allowed students to combine advanced math with chemistry rather than only with physics. They find that taking advanced math course in combination with advanced chemistry course increases earnings by 0.20 log points. However, controlling for post-secondary educational attainment eliminates most of the effect. In contrast, our paper shows that post-secondary choices are path dependent - the courses chosen in high school affects college degree and college major choices and the sequence of choices in turn explains earnings outcomes. Moreover, similar to Joensen and Nielsen (2009), many papers in this area focus on math classes in high school due to limited data availability. The richness of our data allows us to examine the choice of various AP and CTE classes, splitting them into STEM and non-STEM related, hence using a wider set of classes.

Arcidiacono (2004) estimates returns to majors using a structural model to control for selection into majors. He finds large differences in earning premia across majors. Math ability is important both for labor market returns and sorting into particular majors. We similarly find that the choice of classes in high school is important for choosing the path, including the major, as well as the earnings.

Hoekstra (2009) looks at contribution of college quality to earnings. He estimates that attending the most selective state university increases earnings by around 20% for white men. In our data set, we observe the college name and hence are able to control for college quality. We find that attending a high-quality college increases men's wages but decreases women's wages.

Arcidiacono et al. (2016) try to understand why minority students are underrepresented in STEM. They examine data for students who applied to, were admitted to, enrolled at, and/or graduated with a BA degree from one of the University of California campuses in the late '90s. They find that minority students at top ranked campuses would, on average, have significantly higher probabilities of graduating in STEM if they had attended lower ranked campuses. In our estimation, we allow the decision of which major to choose and whether to graduate depend on the college quality, and differently so for different demographic groups. In light of Arcidiacono et al. (2016), it is important to have such flexibility.

2 Model

We describe students' schooling and labor market choices. Our model features forward-looking students who make sequential choices over high-school courses (Node 1), college majors (Node 2), and industries (Node 3). We incorporate unobserved heterogeneity through a latent preference type that governs choices at Nodes 1 and 2, and a separate labor market type that governs the industry choice at Node 3.

2.1 Environment

Students enter the model characterized by an observable state vector X and a latent preference type $\ell \in \{1,\ldots,L\}$. The type ℓ is drawn from a distribution $\pi(\ell \mid X, g)$, where g denotes the student's demographic group (gender or race/ethnicity). The type is fixed across Nodes 1 and 2. It captures heterogeneity in the non-pecuniary utility from different fields of study and in the weight placed on expected future earnings. After finishing their education, students enter the labor market. Beside their observable characteristics X and schooling choices, they are characterized by labor market type.

Students make three sequential choices:

- **Node 1, high school:** Choose an advanced course type $c \in \{1,\ldots,C\}$, where one option c_0 denotes "no advanced courses."
- **Node 2, college:** Choose a major $m \in \{1,\ldots,M\}$, where m_0 denotes "no college".
- **Node 3, labor market:** Choose an industry $j \in \{1,\ldots,J\}$.

We solve the model by backward induction, starting from Node 3.

2.2 Node 3: Labor Market

At the beginning of the labor market stage, a student is characterized by (X, c, m, k), where c and m are the choices from Nodes 1 and 2, and $k \in \{1,\ldots,K\}$ is the labor market type. The labor market type is determined by the school-college path and observable characteristics via a production function $\pi^{(3)}(k \mid X, c, m; g)$, estimated separately for each group g.

The present discounted value of earnings for a worker of type k in group g who chooses industry j is $H_j(X, c, m, k; g)$. In addition to monetary returns, working in industry j yields a systematic amenity a_j and an idiosyncratic amenity ε_j. Workers choose the industry that maximizes total utility:

$$v(X, c, m, k, \varepsilon) = \max_j \left(a_j + H_j(X, c, m, k; g) + \varepsilon_j \right). \tag{1}$$

We assume the shocks ε_j are i.i.d. Gumbel with mean zero and scale parameter ν, independent of all other variables. The ex-ante value function, integrating over ε, is then

$$V^{(3)}(X, c, m, k; g) = \nu \log \left(\sum_j \exp\left(\frac{a_j + H_j(X, c, m, k; g)}{\nu} \right) \right), \tag{2}$$

and the probability of choosing industry j is

$$\lambda^{(3)}(j \mid X,c,m,k;g) = \frac{\exp\left(\dfrac{a_j + H_j(X,c,m,k;g)}{\nu}\right)}{\displaystyle\sum_{j'} \exp\left(\dfrac{a_{j'} + H_{j'}(X,c,m,k;g)}{\nu}\right)}. \tag{3}$$

2.3 Node 2: College and Major Choice

At Node 2, the student has already chosen course type c at Node 1 and is characterized by (X,c,ℓ). After choosing major m, the labor market type k is realized according to the production function $\pi^{(3)}(k \mid X,c,m;g)$.

The expected value from choosing major m is obtained by integrating the Node 3 value function over the distribution of labor market types:

$$V^{(2)}(X,c,m;g) = \sum_{k=1}^{K} \pi^{(3)}(k \mid X,c,m;g)\, V^{(3)}(X,c,m,k;g). \tag{4}$$

A student of type ℓ who chose course c at Node 1 receives utility from major m:

$$U^{(2)}(m \mid X,c,\ell;g) = u^{(2)}_{\ell,m} + \theta^{(2)}_{\ell}\, V^{(2)}(X,c,m;g) + \varepsilon^{(2)}_{m}, \tag{5}$$

where

- $u^{(2)}_{\ell,m}$ is the non-pecuniary utility of major m for type ℓ (normalized: $u^{(2)}_{\ell,m_0} = 0$ for all ℓ),
- $\theta^{(2)}_{\ell} > 0$ is the weight type ℓ places on expected monetary returns at Node 2,
- $\varepsilon^{(2)}_{m}$ is an i.i.d. Gumbel shock with scale 1.

The choice probability at Node 2 is:

$$\lambda^{(2)}(m \mid X,c,\ell;g) = \frac{\exp\left(u^{(2)}_{\ell,m} + \theta^{(2)}_{\ell}\, V^{(2)}(X,c,m;g)\right)}{\displaystyle\sum_{m'} \exp\left(u^{(2)}_{\ell,m'} + \theta^{(2)}_{\ell}\, V^{(2)}(X,c,m';g)\right)}. \tag{6}$$

The ex-ante value of entering Node 2 with course c and type ℓ—the logsum over majors—is:

$$W^{(1)}(\ell,c,X;g) = \log\left(\sum_{m=1}^{M} \exp\left(u^{(2)}_{\ell,m} + \theta^{(2)}_{\ell}\, V^{(2)}(X,c,m;g)\right)\right). \tag{7}$$

2.4 Node 1: High School Course Choice

At Node 1, the student is characterized by (ℓ, X) and chooses course type c. The continuation value of choosing c is $W^{(1)}(\ell, c, X; g)$ from equation (7). The utility from choosing c is:

$$U^{(1)}(c \mid \ell, X; g) = u^{(1)}_{\ell,c} + \theta^{(1)}_{\ell} W^{(1)}(\ell, c, X; g) + \varepsilon^{(1)}_{c}, \tag{8}$$

where

- $u^{(1)}_{\ell,c}$ is the non-pecuniary utility of course c for type ℓ (normalized: $u^{(1)}_{\ell,c_0} = 0$ for all ℓ),
- $\theta^{(1)}_{\ell} \geq 0$ is the weight type ℓ places on the continuation value at Node 1,
- $\varepsilon^{(1)}_{c}$ is an i.i.d. Gumbel shock with scale 1.

The choice probability at Node 1 is:

$$\lambda^{(1)}(c \mid \ell, X; g) = \frac{\exp\Big(u^{(1)}_{\ell,c} + \theta^{(1)}_{\ell} W^{(1)}(\ell, c, X; g)\Big)}{\sum_{c'} \exp\Big(u^{(1)}_{\ell,c'} + \theta^{(1)}_{\ell} W^{(1)}(\ell, c', X; g)\Big)}. \tag{9}$$

2.5 Interpretation of $\theta^{(1)}_{\ell}$ and $\theta^{(2)}_{\ell}$

The parameters $\theta^{(1)}_{\ell}$ and $\theta^{(2)}_{\ell}$ play distinct roles:

- $\theta^{(2)}_{\ell}$ governs how responsive the major choice is to differences in expected earnings and amenities across majors. A high $\theta^{(2)}_{\ell}$ means type ℓ chooses majors primarily based on expected monetary returns.
- $\theta^{(1)}_{\ell}$ governs how forward-looking the high school course choice is. A high $\theta^{(1)}_{\ell}$ means type ℓ chooses courses by anticipating their effect on the value of future options through $W^{(1)}$. If $\theta^{(1)}_{\ell} \approx 0$, course choice is driven entirely by current non-pecuniary preferences $u^{(1)}_{\ell,c}$.
- The product $\theta^{(1)}_{\ell} \cdot \theta^{(2)}_{\ell}$ captures the total responsiveness of Node 1 choices to labor market earnings: a change in $V^{(2)}$ propagates to $W^{(1)}$ and then to Node 1 choice probabilities proportionally to $\theta^{(1)}_{\ell}$.

3 Data

We use a novel Minnesota statewide longitudinal education data (SLEDS) which matches student data from kindergarten through completion of post secondary education and into the workforce. The period of our study is 2003-2019.

The first block of the data comes from Minnesota Department of Education and follow students in K-12 grades. All students in Minnesota public schools are included. The data contains school and district identifiers of the elementary, middle and high school attended by the student, together with standardised test scores in grades 4, 8, and 11. We further see which Advanced Placement (AP) classes and Career and Technical Education (CTE) classes students take in high school. These are advanced courses students can enroll into on top of basic course requirements. We observe several demographic characteristics, such as gender, age, race, language spoken at home, school district of residence, and whether a students receives free or reduced lunch (FRL). In addition, we observe annual attendance for students.

The second block comprises the universe of students attending a college in the state of Minnesota maintained by Minnesota Office of Higher Education. We observe college identifiers, degree that a student enrolls for and achieves, and the choice of major. The pot secondary files also consist of demographic characteristics such as age, gender, race and ethnicity, and citizenship status. We also obtained the National Clearinghouse Data which helps us track students who left Minnesota to attend college in other states. This data set also consists of information on college identifiers, major choice, and degree type.

Finally, the third data set comes from Minnesota Department of Employment and Economic Development and contains the labor market histories of individuals who have ever worked in Minnesota since 2003. For employed workers, we observe quarterly earnings and hours worked, together with establishment and firm identifiers, industry, and location. If an individual is not in the data set for any amount of time, they could either have had an unemployment spell or been self employed for the duration of the absence.

We select cohorts of students who graduated between 2010 and 2014 since these are the cohorts for which we observe test scores in grade 8, high school and college choices, as well as earnings in the first couple of years of their careers. We consider earnings in the first three years after graduation for students who graduate from college and are employed. For high school dropouts or college dropouts, we consider the first three years of employment after the last recorded year of study.

The male-female wage gap in the raw data is 3%. The White-Black, White-Hispanic, and White-Asian wage gaps are 25%, 15%, and 10% respectively. These are the differences in hourly wages we aim to explain in this paper.

3.1 Decision Nodes

We consider 3 time periods where workers make educational and labor market decisions. We refer to these time points as nodes. They are: high school, end of high school, college, and the labor

market.

In Node 1, students choose what type of specialized classes, if any, they want to attend. There are five options, advanced placement (AP) STEM classes, AP non-STEM classes, career and technical education (CTE) STEM classes, and CTE non-STEM classes, or no specialized classes. AP classes are targeted toward students who plan to continue their studies in college, while CTE classes teach specific career skills to high school students. We classify these classes into STEM and non-STEM.

One challenge is that not all high schools offer these specialized classes. To address this issue, we use data from cohorts of high school students in the years before our period of study to identify which schools offered these courses. We then restrict our analysis to these schools.

In node 2, students decide whether to attend college or not. We do not distinguish between students who finish high school but do not go to college and those who drop out of high school because the latter category is very small. Students who go to college can choose between a two-year college or a four year college. Those who choose a two-year college are designated as choosing "some college."

If an individual chooses to go to a four year college, we define four categories based on the quality of college and the major chosen: STEM major in high quality college, STEM major in low quality college, Non-STEM major in high quality college, and Non-STEM major in low quality college. The quality of college is measured using the ACT test scores of all students in the entering cohort of that college. A college is of high quality in our context if the ACT score of that college is above median. Students who enroll in a four-year college but drop out are put in the same category as those going to a two-year college, i.e."some college."

Finally, in Node 3, students enter the labor market and choose one of 9 industries. If an individual does not get a job within the year of graduating, we use the industry of the first job they are employed in. If individuals hold multiple jobs spanning across industries, we use the industry corresponding to their primary job, that is the job where they devote the majority of their work hours.

In the estimation of our model, we merge Nodes 1– Nodes 2 into one decision on school-college path. Node 3 represents the labor market.

3.2 Observable States

The decision of student i in node n is affected by observable state vector X_{in}, $n = 1,\ldots N$. At node $n = 1$, the vector contains five state variables: student cognitive skills, non-cognitive skills, socio-economic status, cultural background, as well as as a measure of quality of student's high school.

We use math test score from middle or elementary school as a proxy for cognitive ability. In particular, within each cohort, we sort students into quartiles using their eighth-grade math scores and use a vector of dummy variables representing this assignment. We proceed similarly for constructing a proxy for non-cognitive skills, using absenteeism instead of math test scores. If eighth grade math score or absenteeism measure is missing, we use other middle or elementary school scores.

We use eligibility for FRPL program as a proxy for socio-economic status and language spoken at home as a proxy for cultural background. There are over 200 different languages represented in our dataset and we categorize them into six language categories: English, Hmong, other Asian, Somali, Spanish, and all other languages.

Finally, we use Value Added Model (VAM) to obtain the distribution of school quality and Empirical Bayes Method to improve the estimates for each school. The ACT scores of students are used to obtain the VAM estimates. We sort high schools into quartiles based on the value added and use the corresponding dummy variables in X. Appendix A provides further details of how we construct school quality measures.

We observe the name of the college that students attend in the data and link it to average math test score of admitted students, the data that are collected by Integrated Post-secondary Education Data System (IPEDS). This data is publicly available. We use this to classify colleges into high-quality (above median) and low-quality (below median).

Table 1: **Summary Statistics: Demographic Characteristics**

		N	Percent Share
Gender	Female	85,516	51
	Male	80,956	49
Race/Ethnicity	White	132,210	79
	Black	13,718	8
	Hispanic	8,942	6
	Asian	11,602	7
Total N		166,472	100

3.3 Descriptive Statistics

There are 166,472 unique individuals born between 1991 and 1996 for whom we observe high school decisions, college decisions, and labor market outcomes. These individuals were in Grade 12 in high school between years 2010 and 2014. Table 1 shows the gender and racial/ethnic com-

position of our sample: there are 51% females and 49% males. The racial and ethnic composition is as follows: 79% whites, 8% blacks, 6% Hispanic, 7% Asians.

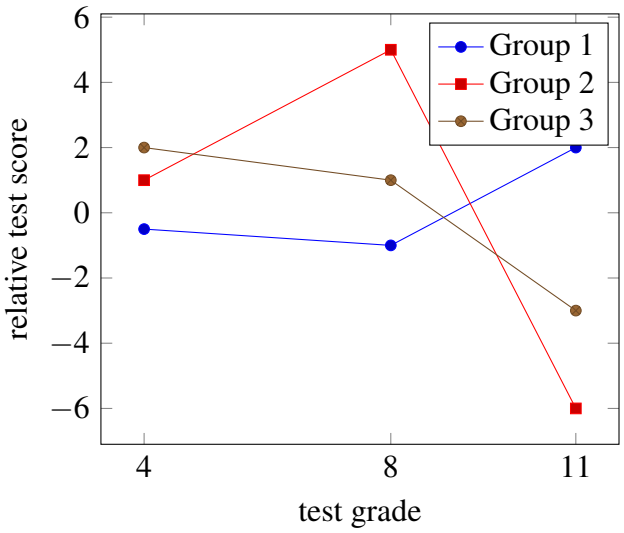
Table 2 shows the summary statistics for observable characteristics by gender and race in our sample. Note that the ability variable is calculated based on test sccores of the entire student population in Minnesota within a cohort, not just the test scores of individuals in our sample. We see that 58% of females and 56% of males in our sample score above median in Grade 8 Maths test in the Minnesota Comprehensive Assessments (MCA) exams.

Table 2: **Observable Characteristics by Gender and Race in Our Sample**

	Females	Males	Whites	Blacks	Hispanics	Asians
Cognitive ability Q4	0.28	0.29	0.33	0.08	0.13	0.20
Q3	0.28	0.29	0.31	0.16	0.21	0.23
Q2	0.25	0.28	0.24	0.28	0.30	0.28
Q1	0.19	0.17	0.13	0.49	0.37	0.29
Non-cognitive ability Q4	0.29	0.28	0.28	0.23	0.22	0.40
Q3	0.28	0.28	0.30	0.22	0.24	0.22
Q2	0.25	0.26	0.27	0.22	0.25	0.18
Q1	0.18	0.18	0.16	0.32	0.29	0.20
School quality Q4	0.26	0.25	0.28	0.13	0.16	0.19
Q3	0.24	0.25	0.27	0.15	0.20	0.15
Q2	0.25	0.25	0.25	0.23	0.22	0.20
Q1	0.25	0.25	0.20	0.49	0.42	0.46
Poor	0.36	0.37	0.27	0.84	0.70	0.71
Non-English speakers	0.10	0.10	0.01	0.21	0.52	0.74
High Quality College	0.26	0.16	0.17	0.09	0.09	0.22

Students, both male and female, are almost uniformly distributed across high schools with different quality, with around 25% of students in each quality quartile. There are however differences across race - 28% of white students is in the highest quality schools compared to just 13% of blacks; conversely, almost 50% of the black students are enrolled in the low-quality schools compared to 20% of white students. Within the non-White group, the average quality of high schools Blacks attend is the lowest. A similar pattern emerges for proportion of students who are poor - male and female proportions are similar at 36% and 37% respectively while the difference between Whites and non-Whites is large. While 27% of Whites are eligible for free and reduced price lunch, the corresponding numbers for Blacks, Hispanics, and Asians are 84%, 70% and 71%.

Figure 1: Evolution of Test Scores for Three Estimated Learning Types



3.4 Learning Types

We use Math test scores for individuals in Grades 4, 8, and 11 and group them based on the evolution of these test scores. We control for age, demographics, FRPL status, homelessness indicator, migrant indicator and language spoken at home. We choose $G = 3$, that is, there are three different learning types. We then use group fixed effects described earlier to estimate assignment of workers into groups.

Figure 1 shows the evolution of the common component of the test score evolution for the three estimated types. For group 1 we observe that, on average, the test scores are relatively stable between elementary and middle schools and then increase sharply in high school. We refer to this group as the 'increasing' learning type. For group 2, the test scores increase in middle school and then decline sharply in high school. This group will be referred to as the 'hump shape' type. Test scores for Group 3 decrease over time and they are thus referred to as the 'decreasing' type.

Table 3 shows the distribution of types by race and gender. The share of males and females that of decreasing type are very similar at 13%. The difference comes from the fact that males are more likely to be of increasing type (48%) while women are more likely to be the hump shaped type (46%). In contrast, for White and Black individuals, the likelihood of being a hump shaped type is similar at 44% and 43% respectively. Relatively, Blacks are more likely to be the decreasing type while Whites are more likely to be increasing type.

For the rest of the paper, we focus our analysis on four demographic groups: females, males, Black individuals, and White individuals.

Table 3: **Learning Productivity Types and Demographics**

	Learning types		
	Increasing	Hump Shape	Decreasing
Female	40.9	46.3	12.8
Male	48.2	39.2	12.6
White	45.3	43.9	10.8
Black	37.9	42.7	19.4
Hispanic	40.9	39.4	19.7
Asian	44.5	33.4	22.1

4 Estimation

We estimate the model in stages, starting from the labor market (Node 3) and working backwards. For each demographic group g, we allow monetary returns to choices to be group-specific, but we restrict non-pecuniary preference parameters $\left\{u^{(1)}_{\ell,c}, u^{(2)}_{\ell,m}, \theta^{(1)}_{\ell}, \theta^{(2)}_{\ell}\right\}$ to be the same across groups. Differences across groups are captured through the type distribution $\pi^{(1)}(\ell \mid X, g)$.

4.1 Node 3: Labor Market

The objects we need to construct are the Node 2 monetary returns $V^{(2)}(X, c, m; g)$ defined in equation (4). To do so, we estimate:

1. $H_j(X, c, m, k; g)$: the present discounted value of earnings,
2. a_j and ν: systematic amenities and the scale of idiosyncratic amenities,
3. $\pi^{(3)}(k \mid X, c, m; g)$: the labor market type production function.

Labor market types and wage equation. We use the AKM regression to estimate worker fixed effects and assign workers into $K = 4$ labor market types k based on these fixed effects. For each type k and group g, we estimate the wage equation

$$\log w_{it}^{g,k} = \gamma_X^{g,k} X + \gamma_m^{g,k} D_m + \gamma_j^{g,k} D_j + \varepsilon_{it}, \tag{10}$$

where X is the vector of initial observable characteristics, D_m is a matrix of dummy variables representing the school-college path choices m, and D_j are industry dummy variables. All coefficients depend on worker type k and group g. This equation describes expected earnings at the beginning of the career.

Present discounted value of earnings. The PDV of log earnings for a worker of type k in group g choosing industry j is:

$$H_j(X,c,m,k;g) = \sum_{a=25}^{T} \beta^{a-25}\Big(g_a^k + \gamma_X^{k,g} X + \gamma_m^{k,g} D_m + \gamma_j^{k,g} D_j\Big), \tag{11}$$

where β is the discount factor and g_a^k is the cumulative earnings growth between ages 25 and a for type k. To estimate g_a^k, we use earlier cohorts in the data with longer labor market histories. For each of the K types identified by the AKM regression in this extended sample, we regress log wages on observable characteristics and a full set of age dummies to recover g_a^k directly.

Amenities and scale parameter. Taking the log-odds of the Node 3 choice probabilities in equation (3) for any two industries j and j' gives:

$$\log \lambda^{(3)}(j \mid X,c,m,k;g) - \log \lambda^{(3)}(j' \mid X,c,m,k;g) = \frac{a_j - a_{j'}}{\nu} + \frac{H_j(X,c,m,k;g) - H_{j'}(X,c,m,k;g)}{\nu}. \tag{12}$$

By the linear specification of H_j, the earnings difference on the right-hand side depends only on the industry coefficients $\gamma_j^{k,g}$, not on (X,c,m). We therefore pool workers across paths and estimate equation (12) using observed industry shares $N^{k,g}(j)$ (number of workers of type k in group g in industry j):

$$\log N^{k,g}(j) - \log N^{k,g}(j_0) = \frac{a_j - a_{j_0}}{\nu} + \frac{1}{\nu}\left(\sum_{a=25}^{T} \beta^{a-25}\right)\left(\gamma_j^{k,g} - \gamma_{j_0}^{k,g}\right), \tag{13}$$

where j_0 is a reference industry with normalization $a_{j_0} = 0$ for all k. The slope coefficient identifies ν and the intercepts identify the relative amenities $a_j - a_{j_0}$.

Node 3 value function and type production function. Given $\hat{H}_j$ and $\hat{\nu}$, we construct the Node 3 value function using equation (2):

$$V^{(3)}(X,c,m,k;g) = \hat{\nu}\log\left(\sum_j \exp\left(\frac{\hat{a}_j + \hat{H}_j(X,c,m,k;g)}{\hat{\nu}}\right)\right).$$

We then estimate the type production function $\pi^{(3)}(k \mid X,c,m;g)$ via multinomial logit at the individual level, since we observe k, X, c, m, and g. This is estimated separately for each group g, so the conditional type distribution is fully group-specific.

This completes the construction of the Node 2 monetary return:

$$V^{(2)}(X,c,m;g) = \sum_{k=1}^{K} \pi^{(3)}(k \mid X,c,m;g)\, V^{(3)}(X,c,m,k;g),$$

as defined in equation (4). Crucially, the no-college/dropout option m_0 is one element of the choice set $\{1,\ldots,M\}$, so $V^{(2)}(X,c,m_0;g)$ and $\pi^{(3)}(k \mid X,c,m_0;g)$ are estimated on the same footing as all other majors, using the observed labor market outcomes of individuals who did not attend college.

4.2 Joint Estimation of Nodes 1 and 2

This is the key estimation step. We observe, for each student i, the course choice c_i, major choice m_i, observable characteristics X_i, and group g_i. We need to estimate the parameter vector:

$$\vartheta \equiv \left\{u^{(1)}_{\ell,c},\ u^{(2)}_{\ell,m},\ \theta^{(1)}_{\ell},\ \theta^{(2)}_{\ell},\ \pi(\ell \mid X,g)\right\}_{\ell,m,c}. \tag{14}$$

Non-pecuniary preference parameters $\{u^{(1)}_{\ell,c}, u^{(2)}_{\ell,m}, \theta^{(1)}_{\ell}, \theta^{(2)}_{\ell}\}$ are restricted to be the same across groups; differences across groups enter through the type distribution $\pi(\ell \mid X,g)$.

4.2.1 Likelihood

Because the latent type ℓ is shared across both nodes, the joint probability of observing the path (c,m) conditional on type ℓ and characteristics X is:

$$P(c,m \mid \ell,X,g;\,\vartheta) = \lambda^{(1)}(c \mid \ell,X;g)\ \lambda^{(2)}(m \mid \ell,c,X;g). \tag{15}$$

Since ℓ is unobserved, the unconditional probability of observing (c,m) is:

$$P(c,m \mid X,g;\,\vartheta) = \sum_{\ell=1}^{L} \pi(\ell \mid X,g)\, P(c,m \mid \ell,X,g;\,\vartheta). \tag{16}$$

The likelihood of the data then is

$$\mathscr{L}(\vartheta) = \sum_i \log \left(\sum_{\ell=1}^{L} \pi(\ell \mid X_i, g_i)\, P(c_i, m_i \mid \ell, X_i, g_i; \vartheta) \right). \tag{17}$$

4.2.2 EM Algorithm

We maximize (17) using an EM algorithm, exploiting the Arcidiacono–Miller (2011) trick.

E-step. Given current estimates $\vartheta^{(t)}$, compute the posterior probability that student i with observed path (c_i, m_i), characteristics X_i, and group g_i is of type ℓ:

$$q^{(t)}(\ell \mid c_i, m_i, X_i, g_i) = \frac{\pi^{(t)}(\ell \mid X_i, g_i)\, P^{(t)}(c_i, m_i \mid \ell, X_i, g_i)}{\sum_{\ell'=1}^{L} \pi^{(t)}(\ell' \mid X_i, g_i)\, P^{(t)}(c_i, m_i \mid \ell', X_i, g_i)}. \tag{18}$$

The posterior uses information from both nodes jointly: a student who chose AP STEM at Node 1 and Engineering at Node 2 provides stronger evidence about their type than either choice alone.

M-step. Given the posteriors $q^{(t)}(\ell \mid c_i, m_i, X_i, g_i)$, solve the system of first-order conditions:

$$0 = \sum_i \sum_{\ell=1}^{L} q^{(t)}(\ell \mid c_i, m_i, X_i, g_i)\, \frac{\partial \log P(c_i, m_i \mid \ell, X_i, g_i; \vartheta)}{\partial \vartheta_j}. \tag{19}$$

Since $\log P(c_i, m_i \mid \ell, X_i, g_i; \vartheta) = \log \lambda^{(1)}(c_i \mid \ell, X_i; g_i) + \log \lambda^{(2)}(m_i \mid \ell, c_i, X_i; g_i)$ by equation (15), the FOCs separate into independent systems for the Node 1 and Node 2 parameters, allowing them to be updated in the M-step. We iterate the E-step and M-step until convergence, running from multiple starting values to avoid local optima. Details of estimation are in Appendix.

4.3 Normalizations

In each node, we introduce one normalization to fix the level of utility:

- **Node 3:** $a_{j_0} = 0$ for a reference industry j_0, for all worker types k. All amenities are relative to this reference.
- **Node 2:** $u^{(2)}_{\ell, m_0} = 0$ for all ℓ, where m_0 is "no college." All major utilities are relative to this option.
- **Node 1:** $u^{(1)}_{\ell, c_0} = 0$ for all ℓ, where c_0 is "no advanced courses." All course utilities are relative to this option.

These normalizations do not affect the counterfactual exercises. The wage counterfactuals (Section 6) operate by changing $V^{(2)}(X,c,m;g)$, which enters the choice probabilities only through differences across alternatives. Specifically, the change in relative utility at Node 2 from a wage counterfactual is

$$\theta_\ell^{(2)}\left[\tilde{V}^{(2)}(X,c,m;g)-\tilde{V}^{(2)}(X,c,m_0;g)\right]-\theta_\ell^{(2)}\left[V^{(2)}(X,c,m;g)-V^{(2)}(X,c,m_0;g)\right],$$

which depends only on identified wage equation coefficients and is unaffected by the normalization $u_{\ell,m_0}^{(2)}=0$.

5 Estimation Results

We estimate the model separately for gender and race. For gender, we have two groups, men and women. For race, we present results for Blacks and White individuals.

5.1 Node 3: Labor Market

We start by reporting results for estimated labor market types. Table 4 shows the distribution of labor market types $k \in \{1,\ldots,4\}$ by demographic group. The distribution is remarkably similar across gender: both males and females have shares of approximately equal shares in types 1 through 4. Note that although we assign workers to types based on quartiles of estimated worker fixed effects—which mechanically produces a uniform distribution in the pooled sample—it does not follow that each demographic group will have a uniform distribution.

The racial comparison reveals a starkly different picture. White workers have a distribution that is close to uniform and slightly tilted toward the highest types. Black workers, by contrast, are heavily concentrated in the lowest-productivity types. This disparity in the productivity type distribution contributes to racial wage gap.

5.1.1 Wage Equation

Table 5 reports wage regression coefficients from equation (10), estimated separately by labor market type k and demographic group. The constant term captures the baseline log wage for workers in the omitted categories (bottom quartile of cognitive ability, not poor, no advanced courses, no college, and the reference industry). The constants increase sharply across types: from 2.55 to 3.10 for females and from 2.60 to 3.16 for males. This confirms that the labor market types capture economically meaningful differences in productivity levels—a worker in Type 4 earns roughly 50–55 log points more than a Type 1 worker at baseline, dwarfing the contribution of any individual

Table 4: Distribution of Labor Market Types by Demographic Group

Group	$k=1$	$k=2$	$k=3$	$k=4$
Female	0.25	0.27	0.25	0.23
Male	0.25	0.27	0.25	0.23
White	0.22	0.25	0.27	0.26
Black	0.38	0.34	0.19	0.09

covariate. The male baseline exceeds the female baseline within every type, with the gap being smallest for Type 1 (0.05 log points) and largest for Type 4 (0.06 log points). For the racial comparison, the constants are very similar between White and Black workers within each type (e.g., 2.54 vs. 2.60 for Type 1, 3.11 vs. 3.14 for Type 4), indicating that once we condition on labor market productivity type, the baseline racial wage gap is small. This will play an important role in Section 6.1 which finds that the racial wage gap operates primarily through who ends up in which type rather than through differential pay within types.

Once we condition on labor market type, cognitive ability has a modest additional effect on wages. The same is true for non-cognitive ability and language spoken at home, which are not displayed here.

The direct wage returns to high school course choices are modest across all groups, consistent with the view that the primary value of AP and CTE courses operates indirectly through their effect on college choices and labor market type.

College choice is where the wage equation coefficients are largest and where gender and racial patterns diverge most sharply. A STEM degree from a high-quality college raises log wages by 22–39 log points for women and 20–32 log points for men, relative to no college, with the premium varying by labor market type. The premium is largest for Type 2 workers for both genders. Strikingly, the college premium is generally larger for women than for men across all college paths and most types. This means that conditional on reaching the same college path and the same labor market type, women earn higher returns to their educational investment than men—a finding that appears to contradict the overall gender wage gap. The resolution lies in the type production function (Table 7): women are less likely to be assigned to the high-productivity types conditional on the same college path, and the baseline wage constants are lower for women within each type. The higher college coefficients for women thus represent a partial offset rather than an overall

advantage.

For the racial comparison, the college premium shows an interesting pattern. Black workers in the highest type receive larger returns to STEM degrees than White workers, though these coefficients are estimated less precisely due to smaller sample sizes. Across lower types, the premium is more similar. The most notable finding is that for Black Type 1 workers, the returns to any college path are small or negative, suggesting that low-productivity Black workers benefit little from college credentials in terms of wages. This may reflect mismatch between education and the types of jobs these workers obtain, or it may indicate that employers discount the college credentials of workers they perceive as low-productivity.

The industry coefficients are broadly similar across gender and race, with construction and finance paying the highest premiums and health services and accommodation the lowest. One noteworthy difference is that the construction premium is larger for men than for women and is largest for the lowest types, consistent with construction offering a wage floor for low-skilled male workers. The health services penalty is larger for men than for women, reflecting the fact that male workers in health services tend to be in lower-paying positions within the sector.

5.1.2 Age-wage profiles

Using earlier cohorts in our data which are not part of our sample, we estimate the age-wage profile for different labor market productivity types. Figure 2 displays the cumulative wage growth between ages 25 and 36 by labor market type. All types experience positive wage growth, but the profiles diverge substantially. Type 4 workers see their wages grow by approximately 80% over this period, while Type 1 workers experience only about 50% growth. The profiles for Types 2 and 3 fall between these extremes. Importantly, the profiles fan out over time: the gap between Type 4 and Type 1 is small at age 26 but widens steadily through age 36, after which we assume flat wages. This divergence implies that the labor market type differences are not important only for early career wages, but also for their subsequent growth. This reflected in the construction of the present discounted value of earnings.

5.1.3 Production function for types

We now turn to the estimate production function of the labor market types. To estimate it, we run a multinomial logit with dummy variables for each category in each variable that describes a worker at the beginning of the labor market, that is, initial characteristics, high school choice and college choice. We omit one category for each variable.

Tables 7 and 8 report the average marginal effects of observable characteristics and path choices on the probability of being assigned to each of the four labor market productivity types, estimated

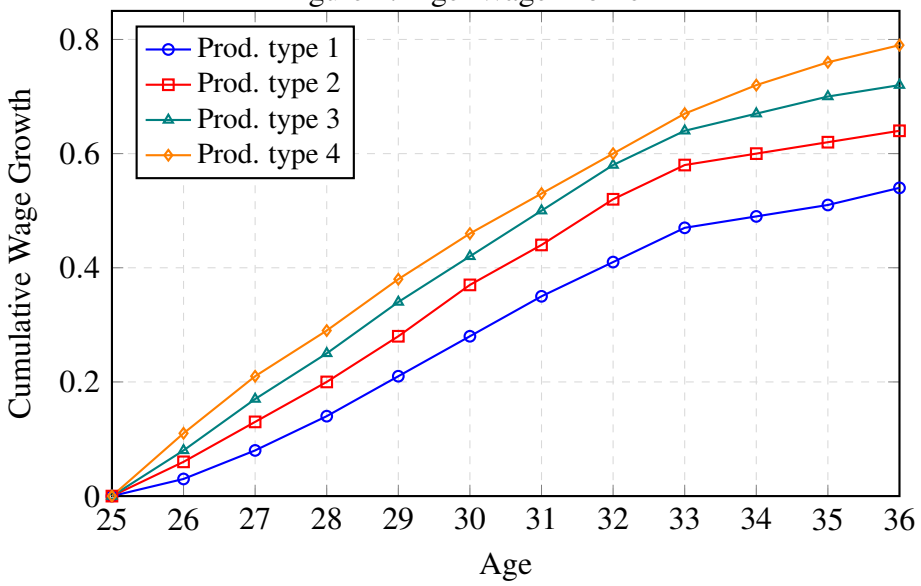
Table 5: Wage regression coefficients (standard errors in parentheses)

		Females				Males			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Cognitive	Q2	0.05	0.04	0.03	0.02	0.03	0.03	0.00	0.00
		(0.01)	(0.01)	(0.02)	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)
	Q3	0.05	0.06	0.04	0.02	0.04	0.04	0.01	−0.01
		(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
	Q4	0.04	0.05	0.04	0.03	0.04	0.02	0.01	0.01
		(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Poor	Yes	−0.04	−0.03	−0.03	−0.04	−0.02	−0.05	−0.04	−0.00
		(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.02)
High school	AP STEM	0.03	0.06	0.04	0.05	0.03	0.03	0.03	0.03
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
	AP NON-STEM	0.03	0.03	0.03	0.02	−0.02	0.01	−0.00	0.01
		(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
	CTE STEM	0.02	0.03	0.03	0.02	0.01	0.02	0.02	−0.01
		(0.00)	(0.00)	(0.01)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)
	AP NON-STEM	−0.01	0.01	0.01	0.01	−0.02	0.01	−0.01	−0.03
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
College	Some college	0.05	0.11	0.09	0.00	−0.03	−0.04	0.08	0.04
		(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
	STEM, low	0.26	0.34	0.31	0.19	0.11	0.11	0.24	0.17
		(0.04)	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
	STEM, high	0.31	0.39	0.38	0.22	0.20	0.21	0.32	0.25
		(0.05)	(0.06)	(0.04)	(0.05)	(0.03)	(0.04)	(0.04)	(0.04)
	NON-STEM, low	0.18	0.26	0.25	0.13	0.06	0.06	0.19	0.13
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.05)
	NON-STEM, high	0.23	0.31	0.32	0.16	0.15	0.16	0.27	0.21
		(0.03)	(0.04)	(0.04)	(0.04)	(0.02)	(0.04)	(0.04)	(0.05)
Industry	Construction	0.08	0.09	0.08	0.02	0.10	0.10	0.11	0.07
		(0.02)	(0.03)	(0.02)	(0.03)	(0.01)	(0.00)	(0.01)	(0.02)
	Manufacturing	0.06	0.02	0.06	−0.00	0.06	0.03	0.05	0.03
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
	Wholesale & retail	−0.05	−0.05	−0.05	−0.05	−0.05	−0.06	−0.06	−0.05
		(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
	Finance	0.12	0.10	0.08	0.04	0.11	0.10	0.06	0.04
		(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
	Education	0.00	0.01	0.00	−0.00	−0.01	0.02	0.01	−0.02
		(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.02)	(0.01)	(0.01)
	Health services	−0.02	−0.04	−0.04	−0.05	−0.04	−0.08	−0.09	−0.07
		(0.00)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
	Accommodation	−0.04	−0.03	−0.04	−0.05	−0.08	−0.08	−0.07	−0.07
		(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)
	Other	−0.00	0.00	−0.01	−0.02	−0.02	−0.01	−0.02	−0.03
		(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
	Constant	2.55	2.52	2.68	3.10	2.60	2.77	2.83	3.16
		(0.04)	(0.01)	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)

Table 6: Wage regression coefficients by race

		White				Black			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Cognitive	Q2	0.04	0.03	0.01	0.01	0.07	0.04	0.05	−0.02
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
	Q3	0.05	0.04	0.03	0.01	0.08	0.11	0.04	−0.03
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)
	Q4	0.04	0.04	0.02	0.02	0.04	0.04	0.03	−0.04
		(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.05)	(0.04)
Poor	Yes	−0.03	−0.04	−0.04	−0.03	−0.04	−0.02	−0.01	0.01
		(0.00)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.04)	(0.04)
High school	AP STEM	0.04	0.05	0.04	0.04	−0.02	−0.00	0.01	−0.03
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.07)
	AP NON-STEM	0.01	0.02	0.01	0.02	0.02	−0.02	0.05	−0.07
		(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.04)	(0.07)
	CTE STEM	0.03	0.04	0.03	0.02	−0.02	0.02	−0.01	−0.14
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)
	CTE NON-STEM	−0.00	0.01	−0.00	−0.01	−0.02	−0.00	−0.02	−0.11
		(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.04)
College	Some college	0.05	0.06	0.07	0.04	−0.05	0.03	0.14	0.10
		(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.06)	(0.11)
	STEM, low	0.22	0.25	0.26	0.19	0.09	0.21	0.26	0.28
		(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.06)	(0.07)	(0.16)
	STEM, high	0.29	0.33	0.33	0.24	0.14	0.26	0.37	0.35
		(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)	(0.08)	(0.16)
	NON-STEM, low	0.17	0.19	0.21	0.14	0.05	0.15	0.22	0.20
		(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.05)	(0.08)	(0.14)
	NON-STEM, high	0.24	0.27	0.29	0.19	0.10	0.20	0.33	0.26
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.09)	(0.14)
Industry	Construction	0.10	0.11	0.13	0.08	0.10	0.10	0.09	0.11
		(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)
	Manufacturing	0.06	0.03	0.06	0.02	0.07	0.01	0.02	0.09
		(0.01)	(0.01)	(0.01)	(0.00)	(0.03)	(0.01)	(0.01)	(0.05)
	Wholesale & retail	−0.06	−0.06	−0.06	−0.05	−0.04	−0.03	−0.03	−0.07
		(0.01)	(0.00)	(0.00)	(0.01)	(0.02)	(0.02)	(0.01)	(0.03)
	Finance	0.11	0.09	0.05	0.04	0.14	0.11	0.11	0.06
		(0.02)	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)
	Education	−0.01	0.00	0.01	−0.01	0.02	0.03	0.01	−0.01
		(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.04)
	Health services	−0.03	−0.06	−0.06	−0.06	−0.01	−0.05	−0.11	−0.10
		(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)
	Accomodation	−0.06	−0.07	−0.06	−0.07	−0.03	−0.03	−0.04	−0.05
		(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.04)
	Other	−0.01	−0.01	−0.01	−0.03	−0.01	0.02	−0.03	−0.06
		(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
	Constant	2.54	2.63	2.76	3.11	2.60	2.59	2.74	3.14
		(0.03)	(0.03)	(0.03)	(0.02)	(0.04)	(0.05)	(0.06)	(0.08)

Figure 2: Age–Wage Profile



separately by gender and race. Type 1 represents the lowest-productivity workers and Type 4 the highest. We highlight the key patterns below.

We compute the average marginal treatment effect on the probability of becoming the given labor market productivity type among treated workers, that is, workers who in the data belong to the category of the variable we examine. All effects are relative to the omitted category.

Cognitive ability. Cognitive ability is the single strongest predictor of labor market type for all demographic groups. Higher math test score quartiles shift probability mass from Type 1 toward Type 4, as expected. However, the magnitude of this effect differs across groups. Among females, moving from the bottom to the top quartile of cognitive ability reduces the probability of being Type 1 by 14.0 pp and increases the probability of being Type 4 by 15.0 pp. For males, the corresponding effects are smaller: -8.8 pp for Type 1 and $+9.8$ pp for Type 4. This indicates that cognitive ability is a stronger differentiator of labor market productivity for women than for men—high-ability women benefit more from their skills, but low-ability women are also penalized more heavily.

The racial comparison reveals a different pattern. For White individuals, the top cognitive quartile reduces the probability of Type 1 by 9.0 pp and increases Type 4 by 11.1 pp. For Black individuals, the effects are larger in both directions: -11.6 pp for Type 1 and $+11.1$ pp for Type 4. The returns to cognitive ability in terms of labor market type assignment are thus at least as large for Black workers as for White workers, suggesting that cognitive skill gaps translate into productivity type gaps roughly proportionally across race. Given that 49% of Black students are in the bottom cognitive quartile compared to 13% of Whites, this channel contributes substantially to the racial

gap in labor market outcomes.

Non-cognitive ability. Non-cognitive ability, proxied by school attendance, has a much weaker effect on labor market type than cognitive ability. For females, the marginal effects of higher non-cognitive quartiles are small and mostly statistically insignificant for Type 4. For males, the pattern is somewhat different: higher non-cognitive quartiles shift probability toward Type 4, with the Q2 effect being 2.0 pp. This suggests that non-cognitive skills matter more for men's labor market productivity than for women's, though the magnitudes are modest.

Across race, the pattern is similarly muted for Whites. For Black individuals, the effects are noisier (reflecting smaller sample sizes) but point in an interesting direction: the top non-cognitive quartile is associated with a decrease in the probability of being Type 4 (-1.3 pp), though this is not statistically significant. Overall, non-cognitive skills play a secondary role relative to cognitive ability in determining labor market type.

School quality. Higher school quality shifts workers toward higher-productivity types for all groups. For females, attending a top-quartile school increases the probability of being Type 4 by 5.5 pp; for males, the effect is 2.1 pp. This is a notable gender difference: women benefit more from school quality in terms of labor market type assignment. One interpretation is that high-quality schools provide resources—such as guidance counseling, advanced coursework, or networks—that are particularly valuable for women's labor market transitions.

For the racial comparison, the effects are roughly similar across White and Black individuals in the upper quartiles (Type 4 effects of 2.4 pp and 3.3 pp for top-quartile schools, respectively). However, for Black students, the third-quartile school quality effect on Type 4 is 3.1 pp, compared to 2.5 pp for Whites. Since nearly half of Black students are currently in bottom-quartile schools, the school quality channel has large potential for improving the distribution of labor market types among Black workers, consistent with the school quality counterfactual results we will see in Section 6.3.

Socioeconomic status. Being eligible for free or reduced-price lunch—our proxy for low socioeconomic status—strongly shifts workers toward low-productivity types. For females, low economic status reduces the probability of being Type 4 by 4.7 pp; for males, the effect is 5.4 pp. The effects are very similar across race: -4.4 pp for Whites and -5.2 pp for Blacks. Given the large gap in poverty rates between White and Black students (27% versus 84%), this factor alone generates a substantial difference in the distribution of labor market types.

Learning types. The unobserved learning types recovered from test score trajectories (Section 3.4) have strong predictive power for labor market productivity. Being of the "decreasing" type (declining test scores from elementary through high school) shifts the distribution sharply toward Type 1 and away from Type 4. For males, the decreasing type increases the probability of Type 1 by 6.7 pp and decreases Type 4 by 7.2 pp. For females, the pattern is similar (6.3 pp and -5.2 pp).

For the racial comparison, the decreasing type penalizes White workers more heavily in terms of Type 4 probability (-7.0 pp) than Black workers (-2.3 pp). However, since Black individuals are nearly twice as likely to be of the decreasing type (19.4% versus 10.8%), the aggregate contribution to the racial gap in type distribution remains substantial.

High school courses. The effect of high school course type on labor market productivity, conditional on all other observables, is relatively modest. For both genders, AP STEM and AP non-STEM courses have small and mixed effects on the type distribution. This may reflect the fact that the effect of high school courses on labor market outcomes operates primarily indirectly through college choices rather than directly through the type production function.

CTE STEM courses show a small positive effect on Type 4 for both genders (about 1 pp), which is consistent with these courses providing directly marketable technical skills. The pattern is similar across race.

College path. The college path variables reveal the starkest differences. Graduating with a STEM major from a high-quality college dramatically increases the probability of being the highest-productivity type. For males, this effect is 15.0 pp; for females, it is 5.9 pp. This is the single largest gender gap in marginal effects across all covariates, and it implies that the same educational investment—a STEM degree from a top college—translates into a much larger labor market productivity gain for men than for women.

For STEM majors at low-quality colleges, the gender gap is also large: 14.1 pp for males versus 2.9 pp for females in the Type 4 effect. Non-STEM majors show a similar pattern but with smaller magnitudes: 6.5 pp for males versus 5.2 pp for females at high-quality colleges, and 6.7 pp versus 10.6 pp at low-quality colleges. Interestingly, for non-STEM majors at low-quality colleges, the Type 4 effect is larger for women than for men, suggesting that this is one path where women's skills are relatively well rewarded in the labor market.

Across race, the patterns are qualitatively similar but differ in magnitude. For White individuals, a STEM degree from a high-quality college increases the probability of Type 4 by 11.3 pp; for Black individuals, the effect is 8.6 pp. The gap is narrower than the gender gap for the same path, suggesting that the racial dimension of the type production function operates more through initial characteristics (which determine who reaches this path) than through differential type assignment

conditional on arriving there. For non-STEM majors at low-quality colleges, the Type 4 effect is substantially larger for Black students (9.1 pp) than for Whites (9.7 pp), and these effects are statistically indistinguishable.

Getting some college education has notably different effects across race. For White individuals, dropping out of college has a modest positive effect on Type 4 (1.7 pp), while for Black individuals it has a smaller effect (1.2 pp). Both are relative to the baseline of not attending college. However, the effect on Type 1 is much larger for Black with some college (-7.0 pp) than for White with some college (-2.8 pp), meaning that Black with some college are substantially less likely to end up in the lowest-productivity type compared to Black individuals who did not attend college at all.

5.1.4 Systematic Amenity for Industries

In the final step of Node 3 estimation, we recover systematic amenity values for different industries a_j and the scale of idiosyncratic amentiy shock ν. We find that for both gender and race, the industry with the lowest amenity value is construction, the industry with the highest amenity is Wholesale, retail, and transportation. The estimated variance of industry amenities a_j/ν provides a measure of how much non-pecuniary factors matter for industry choice relative to earnings. We estimate a variance of a_j/ν equal to 1.60 in the gender specification and 0.86 in the race specification. The higher variance in the gender model suggests that amenity differences across industries play a relatively larger role in explaining in industry sorting compared to the racial differences.

5.2 Nodes 1 and 2: Latent Preference Types

Table 9 reports the estimated preference parameters for the $L = 3$ latent types that govern choices at Nodes 1 (high school) and 2 (college). The parameters $\theta_\ell^{(1)}$ and $\theta_\ell^{(2)}$ capture, respectively, how forward-looking the high school course choice is and how responsive the college major choice is to expected monetary returns in the labor market. The variances of non-pecuniary utilities $u_{\ell,c}^{(1)}$ and $u_{\ell,m}^{(2)}$ measure the dispersion of tastes across alternatives at each node. The last columns report the type distribution $\pi^{(1)}(\ell \mid X, g)$ for the gender and race specifications, averaged over X.

Gender specification. All three types in the gender specification have positive $\theta_\ell^{(1)}$, indicating that high school course choice is at least partly forward-looking for all types. The types differ substantially in the degree of forward-lookingness and responsiveness to returns in the labor market. Type 1 has the lowest values of $\theta^{(1)}\theta^{(2)}$, together with a low variance of non-pecuniary utility at both nodes. This type makes moderately forward-looking course choices and is not very responsive

Table 7: Average Marginal Effect on Treated for $\pi^{(3)}$

		Females				Males			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Cognitive	Q2	−8.27	−2.71	5.29	5.69	−5.03	−3.87	4.57	4.34
		(0.37)	(0.37)	(0.35)	(0.30)	(0.37)	(0.38)	(0.36)	(0.33)
	Q3	−11.20	−5.49	5.21	11.48	−6.90	−3.96	4.65	6.21
		(0.39)	(0.38)	(0.37)	(0.35)	(0.39)	(0.39)	(0.37)	(0.37)
	Q4	−14.00	−5.94	4.98	14.96	−8.76	−4.66	3.67	9.75
		(0.45)	(0.41)	(0.39)	(0.39)	(0.46)	(0.42)	(0.41)	(0.44)
Non-cognitive	Q2	−0.94	−0.91	1.75	0.10	−1.26	−1.02	0.27	2.01
		(0.32)	(0.34)	(0.35)	(0.34)	(0.35)	(0.37)	(0.37)	(0.36)
	Q3	−0.23	−0.25	0.85	−0.37	−1.11	−0.57	−0.26	1.93
		(0.32)	(0.33)	(0.35)	(0.35)	(0.35)	(0.36)	(0.37)	(0.37)
	Q4	0.38	0.04	0.86	−1.28	−1.01	−0.90	0.39	1.52
		(0.33)	(0.34)	(0.35)	(0.36)	(0.35)	(0.36)	(0.37)	(0.38)
School quality	Q2	−3.98	−1.20	1.73	3.45	−3.94	−1.71	1.84	3.81
		(0.36)	(0.37)	(0.38)	(0.36)	(0.37)	(0.39)	(0.39)	(0.38)
	Q3	−4.05	−2.05	1.79	4.31	−3.09	−1.91	1.98	3.03
		(0.35)	(0.36)	(0.38)	(0.37)	(0.37)	(0.38)	(0.39)	(0.39)
	Q4	−3.74	−2.53	0.76	5.51	−1.10	−1.89	0.91	2.08
		(0.36)	(0.36)	(0.39)	(0.41)	(0.38)	(0.38)	(0.40)	(0.43)
Poor		3.18	3.02	−1.46	−4.74	2.33	3.71	−0.65	−5.39
		(0.29)	(0.29)	(0.26)	(0.21)	(0.31)	(0.31)	(0.28)	(0.25)
Language	Spanish	2.55	0.29	−1.45	−1.39	0.52	−0.55	0.87	−0.84
		(0.72)	(0.71)	(0.62)	(0.49)	(0.72)	(0.75)	(0.69)	(0.56)
Learning type	Hump shaped	1.86	−0.48	−0.56	−0.81	3.96	2.05	−0.70	−5.31
		(0.29)	(0.31)	(0.31)	(0.29)	(0.30)	(0.32)	(0.32)	(0.31)
	Decreasing	6.30	1.11	−2.22	−5.19	6.67	2.15	−1.60	−7.22
		(0.27)	(0.28)	(0.28)	(0.26)	(0.28)	(0.29)	(0.29)	(0.28)
High school	AP STEM	2.15	−1.38	−1.12	0.36	0.98	−0.35	−0.85	0.21
		(0.41)	(0.43)	(0.47)	(0.51)	(0.49)	(0.47)	(0.53)	(0.60)
	AP NON-STEM	2.90	−0.94	−0.17	−1.80	1.12	1.16	0.78	−3.06
		(0.44)	(0.46)	(0.49)	(0.50)	(0.57)	(0.57)	(0.60)	(0.61)
	CTE STEM	−0.83	−1.12	0.93	1.02	−3.33	0.83	1.20	1.31
		(0.42)	(0.44)	(0.42)	(0.37)	(0.46)	(0.46)	(0.45)	(0.41)
	CTE NON-STEM	0.44	−0.77	0.43	−0.10	−1.52	1.19	−0.28	0.60
		(0.40)	(0.43)	(0.41)	(0.36)	(0.48)	(0.49)	(0.48)	(0.45)
College	Some college	−2.97	0.12	2.73	0.12	−2.94	−0.37	0.82	2.49
		(0.44)	(0.45)	(0.43)	(0.39)	(0.37)	(0.38)	(0.38)	(0.35)
	STEM, low q.	−0.27	−4.72	2.09	2.90	−8.20	−6.20	0.35	14.06
		(0.79)	(0.78)	(0.82)	(0.82)	(0.59)	(0.61)	(0.66)	(0.68)
	STEM, high q.	2.29	−5.31	−2.92	5.95	−4.50	−8.35	−2.13	14.98
		(0.82)	(0.78)	(0.78)	(0.87)	(0.66)	(0.62)	(0.68)	(0.72)
	NON-STEM, low q	−8.22	−5.91	3.58	10.55	−3.50	−2.98	−0.25	6.72
		(0.45)	(0.48)	(0.49)	(0.52)	(0.45)	(0.46)	(0.48)	(0.48)
	NON-STEM, high q	0.02	−5.30	0.06	5.22	0.83	−4.08	−3.29	6.54
		(0.54)	(0.54)	(0.56)	(0.61)	(0.57)	(0.55)	(0.57)	(0.59)

Table 8: Average Marginal Effect on Treated for $\pi^{(3)}$

		White				Black			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Cognitive	Q2	−5.30	−2.66	3.18	4.78	−3.49	−4.15	5.05	2.60
		(0.33)	(0.34)	(0.33)	(0.31)	(0.72)	(0.70)	(0.59)	(0.41)
	Q3	−7.06	−3.73	2.85	7.94	−7.29	−3.99	5.68	5.61
		(0.33)	(0.33)	(0.33)	(0.32)	(0.91)	(0.89)	(0.77)	(0.62)
	Q4	−8.99	−4.47	2.40	11.06	−11.63	−5.56	6.07	11.12
		(0.38)	(0.35)	(0.34)	(0.35)	(1.26)	(1.23)	(1.13)	(1.04)
Non-cognitive	Q2	−0.72	−0.25	0.65	0.32	−0.36	−0.91	−0.27	1.55
		(0.28)	(0.29)	(0.30)	(0.30)	(0.80)	(0.79)	(0.68)	(0.50)
	Q3	−0.83	0.48	0.06	0.28	1.53	−1.74	−0.86	1.07
		(0.28)	(0.29)	(0.30)	(0.31)	(0.81)	(0.80)	(0.70)	(0.54)
	Q4	−0.54	0.08	0.66	−0.20	3.78	−0.63	−1.85	−1.30
		(0.28)	(0.29)	(0.31)	(0.32)	(0.82)	(0.81)	(0.73)	(0.57)
School quality	Q2	−2.10	−1.69	1.11	2.68	−3.56	−0.24	2.18	1.62
		(0.33)	(0.35)	(0.35)	(0.35)	(0.78)	(0.76)	(0.65)	(0.46)
	Q3	−1.47	−2.34	1.33	2.47	−5.95	1.25	1.62	3.07
		(0.32)	(0.34)	(0.35)	(0.35)	(0.79)	(0.79)	(0.67)	(0.52)
	Q4	−0.54	−2.11	0.27	2.38	−2.45	−3.62	2.74	3.33
		(0.32)	(0.33)	(0.35)	(0.37)	(0.89)	(0.85)	(0.77)	(0.63)
Poor		0.53	3.10	0.75	−4.37	4.45	3.17	−2.37	−5.24
		(0.22)	(0.24)	(0.23)	(0.21)	(0.91)	(0.90)	(0.72)	(0.53)
Language	Spanish	−4.07	−3.59	7.51	0.15	−3.93	10.07	−5.43	−0.71
		(5.98)	(6.51)	(7.27)	(6.38)	(8.80)	(9.23)	(6.39)	(4.67)
Learning type	Hump shaped	2.52	1.31	−0.36	−3.47	2.62	−1.50	0.08	−1.20
		(0.23)	(0.25)	(0.26)	(0.26)	(0.79)	(0.78)	(0.66)	(0.48)
	Decreasing	6.44	2.30	−1.71	−7.04	5.15	−0.95	−1.86	−2.34
		(0.21)	(0.23)	(0.23)	(0.23)	(0.73)	(0.72)	(0.59)	(0.43)
High school	AP STEM	1.66	−0.67	−1.15	0.15	1.42	−1.08	−0.32	−0.03
		(0.36)	(0.36)	(0.40)	(0.44)	(1.33)	(1.29)	(1.25)	(1.18)
	AP NON-STEM	2.45	0.21	0.08	−2.74	3.01	−1.92	0.37	−1.46
		(0.40)	(0.41)	(0.44)	(0.46)	(1.31)	(1.26)	(1.18)	(0.96)
	CTE STEM	−1.76	−0.61	0.90	1.46	−1.69	1.37	0.70	−0.38
		(0.35)	(0.37)	(0.37)	(0.35)	(0.94)	(0.92)	(0.74)	(0.52)
	CTE NON-STEM	0.48	0.29	−0.18	−0.60	0.25	−0.37	0.48	−0.37
		(0.35)	(0.38)	(0.38)	(0.36)	(0.98)	(0.96)	(0.77)	(0.54)
College	Some college	−2.80	−0.62	1.76	1.65	−6.99	1.72	4.04	1.22
		(0.33)	(0.35)	(0.35)	(0.33)	(0.87)	(0.83)	(0.65)	(0.46)
	STEM, low q	−4.71	−6.39	0.72	10.38	−10.86	−1.23	8.37	3.71
		(0.52)	(0.54)	(0.57)	(0.60)	(2.23)	(2.15)	(2.01)	(1.48)
	STEM, high q	−1.71	−7.47	−2.17	11.34	−6.02	−7.64	5.12	8.55
		(0.57)	(0.55)	(0.58)	(0.63)	(2.67)	(2.34)	(2.29)	(2.02)
	NON-STEM, low q	−5.80	−5.48	1.60	9.67	−15.30	−1.45	7.68	9.08
		(0.36)	(0.38)	(0.39)	(0.40)	(1.16)	(1.12)	(0.99)	(0.84)
	NON-STEM, high q	0.87	−5.18	−1.97	6.28	−6.52	−4.22	5.02	5.72
		(0.44)	(0.44)	(0.45)	(0.47)	(1.54)	(1.41)	(1.30)	(1.13)

Table 9: Estimated Preference Type Parameters

		$\theta^{(1)}\theta^{(2)}$	$Var[u^{(1)}_{\ell,c}]$	$Var[u^{(2)}_{\ell,m}]$	$\pi^{(1)}(l)$	
Gender					female	male
	$l=1$	1.14	0.70	1.48	0.29	0.26
	$l=2$	1.72	0.86	7.83	0.43	0.38
	$l=3$	3.06	5.54	58.74	0.27	0.36
Race					white	black
	$l=1$	0.86	0.79	0.71	0.31	0.12
	$l=2$	0.00	0.55	11.18	0.44	0.31
	$l=3$	0.00	4.25	52.90	0.25	0.58

to earnings differences across majors—choices are driven by a combination of tastes and monetary considerations, but neither dominates.

Type 2 is more forward-looking ($\theta^{(1)} = 1.72$) and places moderate weight on monetary returns at Node 2 ($\theta^{(2)} = 0.86$). The variance of non-pecuniary utility at Node 2 is substantially higher (7.83), indicating that this type has strong and dispersed preferences over high school course types. Type 2 is the most common type among both females (share 0.43) and males (0.38).

Type 3 stands out with a markedly high $\theta^{(1)}\theta^{(2)}$ of 3.06, meaning this type's high school and college major choices are very responsive to expected labor market returns. The product $\theta^{(1)}_3 \cdot \theta^{(2)}_3$ captures the total responsiveness of Node 1 choices to labor market earnings: changes in earnings propagate strongly back to high school decisions for this type. However, the variance of non-pecuniary utility at Node 1 and Node 2 is very large, suggesting that even for this earnings-responsive type, there is substantial heterogeneity in intrinsic preferences over courses. Type 3 is very common type among males (share 0.36) and less common among females (0.27).

The difference in type distributions across gender is informative. Males are more likely than females to be the highly earnings-responsive type ($\ell = 3$), while females are more likely to be the moderate type ($\ell = 2$) with strong but dispersed course preferences.

Race specification. The race specification reveals a strikingly different pattern. Types 2 and 3 both have $\theta^{(1)}_\ell \theta^{(2)}_\ell \approx 0$, meaning that for these types, high school course choice is entirely myopic—it is driven solely by current non-pecuniary preferences $u^{(1)}_{\ell,c}$ and $u^{(2)}_{\ell,m}$, and is unresponsive to the continuation value in later nodes. Only Type 1, with $\theta^{(1)} = 0.86$, exhibits any forward-looking behavior at Node 1 and 2.

Table 10: Estimated Non-pecuniary Utilities in Node 1 and 2

	Gender			Race		
	type 1	type 2	type 3	type 1	type 2	type 3
Node 1						
AP STEM	1.84	-1.21	-4.80	1.98	-0.05	-3.31
AP NON-STEM	1.28	0.37	-2.23	1.26	0.44	-2.15
CTE STEM	-0.04	0.56	-0.11	-0.07	1.50	1.39
CTE NON-STEM	0.36	1.32	1.13	0.37	1.36	1.09
None	0.00	0.00	0.00	0.00	0.00	0.00
Node 2						
No college	0.00	0.00	0.00	0.00	0.00	0.00
Some college	1.95	5.74	0.76	1.84	5.59	0.79
STEM Major, low quality college	-1.06	1.67	-16.77	0.97	-0.49	-17.98
STEM Major, high quality college	-1.43	-1.84	-7.35	1.26	-4.37	-9.11
NON-STEM Major, low quality college	0.61	4.50	-5.41	2.18	2.77	-12.43
NON-STEM Major, high quality college	0.29	2.39	-16.38	2.17	0.33	-9.72

Type $\ell = 2$ and $\ell = 3$ differ in how dispersed their non-pecuniary returns are. They are very dispersed for $\ell = 3$ and so this type's choices are mostly based on preferences for different type courses.

The type distribution differs sharply between White and Black individuals. A majority of Black individuals (58%) are assigned to Type 3, which has very low $\theta^{(1)}\theta^{(2)}$ and a very high variance of non-pecuniary utility at both nodes. For these individuals, high school course choice and college majors are entirely taste-driven and do not anticipate future educational or labor market consequences. In contrast, only 25% of White individuals are of this type, while 31% are Type 1—the only type with forward-looking course choice. Among Black individuals, only 12% are Type 1.

5.3 Non-Pecuniary Utilities

Table 10 reports the estimated non-pecuniary utilities for each latent preference type, normalized relative to "no advanced courses" at Node 1 and "no college" at Node 2. The parameters are restricted to be the same across demographic groups within each specification; differences across groups in path choices therefore arise entirely from the type distribution $\pi^{(1)}$ and from group-specific monetary returns $V^{(2)}$.

At Node 1, the three types are sharply differentiated in their tastes for academic versus vocational courses. Type 1 has a strong preference for AP courses, especially AP STEM (1.84 in the gender specification, 1.98 in the race specification), and is roughly indifferent between CTE options and no advanced courses. Type 2, by contrast, favors CTE courses—particularly CTE non-STEM (1.32)—and is nearly indifferent toward AP courses. Type 3 has large negative non-pecuniary utility for AP STEM in the gender and race specification, and moderate disutility for AP non-STEM, while being roughly neutral toward CTE and no-course options. Given that Type 3 is the most earnings-responsive type in gender specification, the strongly negative taste for AP STEM means that even highly earnings-motivated students may avoid AP STEM courses unless the monetary payoff is large enough to overcome this non-pecuniary cost. Since males are disproportionately Type 3, this creates an interesting tension: men are more responsive to earnings but also have stronger distaste for the academic courses that lead to high-earning STEM paths.

At Node 2, the non-pecuniary utilities reveal why college major choice is the critical node for wage gaps. All college options have large negative non-pecuniary utilities for Type 3—the most earnings-responsive type—with STEM majors at low-quality colleges being especially unattractive. Since Type 3 also has the highest weight on continuation value, the college major decision for this type is driven by a tension between strong monetary incentives to choose STEM and large non-pecuniary costs of doing so. Type 2 displays the opposite pattern: it has moderately positive non-pecuniary utility for most college options, particularly some college and non-STEM at low-quality colleges, but a low weight on monetary returns. This type chooses college paths primarily on the basis of tastes rather than earnings. Type 1 has relatively balanced preferences across college options, with small positive values for some college and non-STEM paths and small negative values for STEM paths.

5.4 Model Fit

Finally, in Appendix B, we show the predicted and actual distribution of students in Nodes 1 and 2. We observe that the model explains the data well.

6 Counterfactual Exercises

Our estimated model allows us to decompose the sources of wage gaps across demographic groups and to evaluate the effects of policy interventions. We conduct three sets of counterfactual exercises. First, we decompose the initial wage gap into contributions from the distribution of observable and unobservable types, returns to skills, and path choice. Second, we evaluate the effect of encouraging STEM education at different nodes of the decision tree. Third, we examine the effect

of improving school quality for disadvantaged students.

6.1 Counterfactual I: Decomposing the Initial Wage Gap

We begin by decomposing the wage gap into its structural sources. The average wage for group g can be written as

$$\bar{w}_g = \frac{1}{N_g} \sum_{(x,c,m,j,k)} w_g(x,c,m,j;k)\, N_g(x,c,m,j,k), \tag{20}$$

where the share of workers with characteristics (x,c,m,j,k) in group g is given by

$$\begin{aligned} \frac{N_g(x,c,m,j,k)}{N_g} = \pi_g^{(0)}(x) & \\ \times \left(\sum_{\ell} \lambda_g^{(1)}(c \mid x)\, \lambda_g^{(2)}(m \mid x,c,\ell)\, \pi_g^{(1)}(\ell \mid x) \right) & \\ \times \lambda_g^{(3)}(j \mid x,c,m)\, \pi_g^{(3)}(k \mid x,c,m). & \end{aligned} \tag{21}$$

This expression makes explicit the five channels through which groups can differ in average wages: (i) the distribution of observable initial characteristics $\pi_g^{(0)}(x)$, (ii) the distribution of latent preference types $\pi_g^{(1)}(\ell \mid x)$, (iii) the distribution of labor market productivity types $\pi_g^{(3)}(k \mid x,c,m)$, (iv) the group-specific returns to skills embodied in $w_g(x,c,m,j;k)$, and (v) the path choices $\lambda_g^{(\cdot)}$ at each node.

To isolate the contribution of each channel, we conduct a series of counterfactual exercises in which we replace one component of the disadvantaged group with the corresponding component of the benchmark group while holding all other components fixed. Crucially, when we replace any of the structural objects in columns (2)–(5) of Table 11—that is, the distribution of observables $\pi^{(0)}$, the preference type distribution $\pi^{(1)}$, the labor market type distribution $\pi^{(3)}$, or the wage equation returns—we re-solve the model to obtain new equilibrium path choices $\lambda^{(\cdot)}$. This allows individuals to re-optimize their school-college-career decisions in response to the changed environment. In column (6), by contrast, we directly assign the benchmark group's path choices $\lambda^{(\cdot)}$ to the other group without re-solving the model, holding the distribution of types and returns unchanged. This exercise isolates the mechanical contribution of path differences to the wage gap.

Table 11 presents the results. The benchmark gender wage gap implied by our estimated model is 2.6 percentage points. Several patterns emerge from the decomposition.

Gender wage gap. For gender, the most striking finding is in column (5): when we give females the same returns to skills as males and allow them to re-optimize their path choices, the wage gap becomes -0.3 percentage points—that is, females would earn slightly more than males. This

Table 11: Counterfactual Decomposition of Initial Wage Gap

Group	wage gap (1)	$\pi^{(0)}(x)$ (2)	$\pi^{1}(l\|x)$ (3)	$\pi^{3}(k\|x)$ (4)	returns (5)	$\lambda^{(\cdot)}$ (6)
Male - Female	2.6	4.8	5.6	2.1	-0.3	3.2
White - Black	21.4	10.0	61.6	16.8	16.3	21.6

Notes: Column (1) reports the benchmark wage gap implied by the estimated model. Columns (2)–(5) report the counterfactual wage gap when the indicated component of the disadvantaged group is replaced with that of the benchmark group and the model is re-solved to obtain new path choices. Column (6) reports the counterfactual wage gap when the path choices of the benchmark group are directly assigned to the other group without re-solving. All values are in percentage points.

implies that the entire gender wage gap, and then some, is attributable to females facing lower returns to the same characteristics and choices. Interestingly, when females are given the same returns, their re-optimized path choices lead them to paths that, combined with male-level returns, yield higher wages than males themselves achieve.

Columns (2) through (4) show that equalizing the distribution of observable characteristics, preference types, or labor market types actually increases the gender gap. This indicates that the current distribution of these endowments partially offsets the gender gap: on average, women have slightly more favorable observable characteristics and type distributions than men, which mitigates what would otherwise be a larger gap arising from differential returns.

Column (6) shows that directly assigning male path choices to females increases the gap slightly from 2.6 to 3.2 pp. This seemingly paradoxical result reflects the fact that women's current path choices—conditional on their endowments and the returns they face—are actually advantageous relative to men's paths. In other words, women are making choices that partially compensate for the lower returns they face. If they instead followed men's paths while still receiving female returns, they would be worse off.

Taken together, these results paint a clear picture for gender: the initial wage gap is driven almost entirely by differential returns to the same skills and paths, not by differences in endowments or in the paths chosen.

White-Black wage gap. The decomposition for the White-Black wage gap tells a very different story. The benchmark gap is 21.4 percentage points, substantially larger than the gender gap. Unlike gender, all channels contribute meaningfully to the racial gap.

Equalizing the distribution of observable initial characteristics (column 2) reduces the gap by more than half, from 21.4 to 10.0 pp. This underscores the importance of pre-high-school factors—cognitive ability, non-cognitive ability, school quality, socioeconomic status, and cultural background—in explaining racial wage differences. Recall from Table **??** that 49% of Black students are in the lowest quartile of cognitive ability and 49% attend the lowest-quality high schools, compared to 13% and 20% of White students, respectively. These initial disadvantages propagate through the entire school-college-career path.

The preference type distribution also plays a large role: equalizing $\pi^{(1)}(\ell \mid x)$ across race produces a counterfactual gap of 61.6 pp (column 3), which is much larger than the benchmark gap. This counterintuitive result reflects the fact that the current type distribution of Black individuals is, conditional on their observable characteristics, relatively favorable. As discussed in Section 5.2, 58% of Black individuals are of Type 3, which has $\theta^{(1)}\theta^{(2)} = 0$ (myopic at Nodes 1 and 2). If Black individuals instead had the White type distribution—with a larger share of types that have moderate $\theta^{(1)}\theta^{(2)}$ and higher non-pecuniary variance—the model predicts they would make choices less well-aligned with monetary returns at the college stage, widening the gap.

Equalizing labor market productivity types (column 4) reduces the gap modestly to 16.8 pp. Equalizing returns (column 5) also yields a reduction, to 16.3 pp, indicating that about a quarter of the racial gap is due to Black workers receiving lower returns to the same characteristics and paths. While meaningful, this is far smaller than the returns effect for gender, where equalizing returns eliminated the entire gap.

Finally, directly assigning White path choices to Black individuals (column 6) barely changes the gap (from 21.4 to 21.6 pp). This confirms that differential path choices play almost no role in the racial wage gap—the gap is driven primarily by differences in initial endowments and, to a lesser extent, by differential returns.

6.2 Counterfactual II: Encouraging STEM Education

A prominent policy adopted for reducing wage gaps is to encourage students—particularly women and minorities—to pursue STEM fields. Our structural model allows us to evaluate this proposal by simulating the effect of reducing the non-pecuniary costs of STEM education.

Specifically, we increase the non-pecuniary utility of STEM options by one-fifth of a standard deviation of $u^{(\cdot)}$, applied at Node 1 (high school STEM courses), at Node 2 (STEM college majors), or at both nodes simultaneously. This subsidy can be interpreted as representing policies such as mentoring programs, changes in departmental culture, improved exposure to STEM fields, or targeted financial aid for STEM programs. We apply the subsidy universally to all demographic groups and re-solve the model to obtain new equilibrium path choices.

Table 12 reports the change in the share of STEM majors (Δn_{STEM}) and the change in average wages ($\Delta \bar{w}$) for each group, as well as the resulting wage gap.

Table 12: Counterfactual II: Encouraging STEM Education

	Node 1		Node 2		Node 1 & 2	
	Δn_{STEM}	Δw	Δn_{STEM}	Δw	Δn_{STEM}	Δw
Male	0.01	0.19	2.4	0.30	2.4	0.50
Female	0.01	0.15	2.2	0.24	2.2	0.38
Male - Female		2.64		2.66		2.72
White	0.01	0.28	6.4	0.79	6.4	1.08
Black	0.01	0.01	2.8	0.29	2.8	0.31
Black - White		21.47		21.90		22.17

Notes: The subsidy increases non-pecuniary utility of STEM options by one-fifth of a standard deviation of $u^{(\cdot)}$ at the indicated node(s). The subsidy is applied universally across all groups. Δn_{STEM} is the change in the share of individuals choosing STEM majors (in percentage points). $\Delta \bar{w}$ is the change in average log wages within the group (in percentage points). The wage gap row reports the counterfactual gap after the intervention.

Three findings stand out. First, the Node 1 intervention (subsidizing STEM courses in high school) has almost no effect on either STEM major shares or wages for any group. The change in STEM major shares is 0.01 pp for all groups, and the wage increases are negligible. This is consistent with the estimated preference parameters: in the race specification, two of three types have $\theta_\ell^{(1)} \approx 0$, meaning their high school course choice is completely unresponsive to changes in the continuation value. Even in the gender specification, where all types have positive $\theta^{(1)}\theta^{(2)}$, the effect of a Node 1 subsidy is modest.

Second, the Node 2 intervention (subsidizing STEM majors directly) is substantially more effective. Among males, the share choosing STEM majors increases by 2.4 pp and average wages rise by 0.30 pp. Among females, the corresponding numbers are 2.2 pp and 0.24 pp. For race, the contrast is starker: White students increase STEM enrollment by 6.4 pp with a wage gain of 0.79 pp, while Black students increase by 2.8 pp with only 0.29 pp in wage gains. The smaller response among Black students reflects two factors: (i) the distribution of initial characteristics places more Black students at nodes where STEM is less accessible (fewer have high cognitive scores and attend high-quality colleges), and (ii) the type distribution means a smaller share of Black students are on the margin of switching into STEM.

The universal STEM subsidy does not reduce wage gaps—it increases them. The gender gap rises from the benchmark of 2.6 pp to 2.72 pp when the subsidy is applied at both nodes. The White-Black gap rises from 21.4 pp to 22.17 pp. The mechanism is straightforward: because males and White students respond more strongly to the STEM subsidy (due to differences in type distributions and initial characteristics), a universal subsidy disproportionately benefits the already-advantaged group. This finding has a clear policy implication: universal STEM encouragement programs, applied equally across demographic groups, are unlikely to close wage gaps and may in fact widen them.

6.3 Counterfactual III: Improving School Quality

Given the large contribution of initial characteristics to the racial wage gap documented in Section 6, we examine a targeted intervention that improves school quality for students in the lowest-quality schools. Specifically, we move all students currently in the first (bottom) quartile of school quality to the third quartile. We then re-solve the model: the change in observable characteristics X affects the continuation values $V^{(2)}(X,c,m;g)$ and the labor market type production function $\pi^{(3)}(k \mid X,c,m;g)$, which in turn alter path choices at both nodes.

Table 13 reports the change in average wages within each group.

Table 13: Counterfactual III: Improving School Quality

	Female	Male	White	Black
Change in average wage	0.7	0.7	0.6	1.8

Notes: Students in the bottom quartile of school quality are moved to the third quartile. The model is re-solved to obtain new path choices given the updated observable characteristics. Changes are in percentage points.

The results show that improving school quality raises wages for all groups, but the effect is three times larger for Black students (1.8 pp) than for White students (0.6 pp). This asymmetry arises because a much larger share of Black students is affected by the intervention: 49% of Black students are in bottom-quartile schools compared to 20% of White students. Furthermore, the effect of school quality improvement operates through multiple channels: it directly affects the returns to education (through higher-quality instruction and resources), it changes the feasible set of college options (higher school quality is associated with better college matches), and it shifts the distribution of labor market types (students from higher-quality schools are more likely to be assigned to higher-productivity types).

When this intervention is applied to all students, it has equal effect on males and females, increasing the average wage within each group by 0.7 pp each. The implication is that school quality interventions would not affect the gender wage gap, as both average wages increase by the same amount.

This intervention has a differential effect on White and Black students, leading to an increase of 1.8 pp for Black students, and 0.6pp for White students. Overall, this would decrease the racial wage gap by 1.2 pp ($= 1.8 - 0.6$).

The magnitude of this reduction is modest relative to the total White-Black gap of 21.4 pp. Given the decomposition result where equalizing initial characteristics between white and black decreased the wage gap by more than 11.4pp, one could have expected a larger impact. This exercise implies that it is the joint distribution of initial characteristics that matters, and addressing school quality without addressing cognitive skills, socioeconomic background, and other initial disadvantages would yield small effects.

6.4 Discussion

The three counterfactual exercises reveal a fundamental asymmetry in the sources of gender and racial wage gaps. The gender gap is driven almost entirely by differential returns: women receive lower compensation for the same characteristics and choices, and this gap persists even though women make path choices that partially compensate for the lower returns they face. Policies aimed at changing women's educational choices, such as universal STEM encouragement, would not close the gap and could widen it.

The racial gap, by contrast, has multiple sources. Differences in initial endowments account for over half of the gap, with the joint distribution of cognitive ability, school quality, and socioeconomic status being particularly important. Differential returns explain about a quarter of the gap, and path choices play essentially no role. The implication is that reducing the racial gap requires upstream interventions—improving school quality, early childhood education, and the socioeconomic conditions of minority families—rather than interventions targeted at the college or labor market stage. Universal STEM encouragement is particularly ineffective for closing the racial gap, as White students respond more strongly than Black students due to differences in initial characteristics and type distributions.

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Appendix

A. Measure of School Quality

In this section, we describe the measure of school quality used in our analysis. Since we have observational data from all school districts in Minnesota, where none of the districts use a centralized school assignment or fully use a lottery based system for seats, we use a Value Added Model (VAM) to obtain the distribution of school quality and Empirical Bayes Method to improve the estimates for each school. Deming (2014) finds that VAMs have accurate out-of-sample prediction of student achievement and he fails to reject the hypothesis that school effects estimated using VAM are unbiased.

Consider a population of students indexed by i, each attending one of J schools in a district in Minnesota. Let $Y_{i(j)}$ denote student i's potential academic achievement if she attends school $j \in \{1,...,J\}$. Let D_{ij} indicate attendance at school j and X_i denote a vector of covariates. The observed outcome is:

$$Y_i = \sum_j \alpha_j D_{ij} + \varepsilon_i \tag{22}$$

where, α_j is the value-added of school j and ε_i is the unobserved student heterogeneity such that $\varepsilon_i \sim \mathcal{N}(0, \sigma_\varepsilon^2)$. The identifying assumption is that X_i captures all selection bias, such that $E[D_{ij}\varepsilon_i] = 0 \; \forall j$. This allows us to use ordinary least squares to estimate value added for each school $\hat{\alpha}_j$ and its standard error s_j.

The estimates obtained above can have substantial sampling errors for small schools with relatively few student observations. We use Empirical Bayes method that uses the full set of VAM estimates $\hat{\alpha}_j$ to reduce sampling variance in individual school quality estimates. Suppose we have the following hierarchical model:

$$\hat{\alpha}_j | \alpha_j, s_j \sim \mathcal{N}(\alpha_j, s_j^2)$$

$$\alpha_j \sim G(\alpha), \qquad j = 1,...,J$$

where G is a mixing distribution. We will first use $\{\hat{\alpha}_j, s_j\}_{j=1}^J$ to get an estimate of the mixing distribution $\hat{G}$. We will then treat $\hat{G}$ as a prior and update $\{\hat{\alpha}_j, s_j\}_{j=1}^J$ to get the posterior estimate of our school value added measure $\{\hat{\alpha}_j^*\}_{j=1}^J$.

Under the parametric assumption that $\alpha_j \sim \mathcal{N}(\mu_\alpha, \sigma_\alpha^2)$, the posterior value added measure for school j is

$$\hat{\alpha}_j^{PEB} = \hat{\alpha}_j \frac{\hat{\sigma}_\alpha^2}{\hat{\sigma}_\alpha^2 + s_j^2} + \hat{\mu}_\alpha \frac{s_j^2}{\hat{\sigma}_\alpha^2 + s_j^2};$$

where, $\hat{\mu}_\alpha$ and $\hat{\sigma}_\alpha^2$ can be obtained using method of moments: $\hat{\mu}_\alpha = \frac{1}{J}\sum_{j=1}^J \hat{\alpha}_j$ and $\hat{\sigma}_\alpha^2 = \frac{1}{J}\sum_{j=1}^J [(\hat{\alpha}_j - \hat{\mu}_\alpha)^2 - s_j^2]$.

Imposing normality assumption on G can lead to specification error. To avoid this, we obtain nonparametric Bayes estimator for school value added using methodology similar to Gilraine, Gu, and McMillan (2020). The distribution G can be estimated nonparametrically from the data via the following optimization:

$$\hat{G} \equiv \underset{G \in \mathbb{G}}{\operatorname{argmax}} \left\{ \sum_{j=1}^J log \int \varphi_j(y_j - \alpha) dG(\alpha) \right\} \tag{23}$$

where φ_j is a normal density with mean zero and variance σ_ε^2/n_j. The state space $\mathbb{G}$ is the set of all probability distributions in $\mathbb{R}$. We follow Koenker and Mizera (2014) by estimating $\hat{G}$ from a finite-dimension convex approximation of the above problem. Let M be a positive integer and let $\mathbb{G}_M$ be the class of probability distribution functions supported on M grid points given by $min_j\{\hat{\alpha}_j\} < \alpha_1 < \alpha_2 < ... < \alpha_M < max_j\{\hat{\alpha}_j\}$. The nonparametric maximum likelihood estimator is then defined to be the maximizer of equation 23 when $\mathbb{G}$ is replaced by $\mathbb{G}_M$. We take M to be

the square-root of the sample size.

We use $\hat{G}$ estimated from the above exercise to obtain the nonparametric empirical Bayes estimator for the school value added:

$$\hat{\alpha}_j^{NPEB} = \frac{\int \alpha \varphi_j(y_j - \alpha) d\hat{G}(\alpha)}{\int \varphi_j(y_j - \alpha) d\hat{G}(\alpha)}.$$

B. Fit of the Model in Nodes 1 and 2

Table 14 shows predicted and actual shares of joint choices in Nodes 1 and 2. The model explains the data very well.

Table 14: Predicted shares in Nodes 1 and 2 for different demographic groups

		Females		Males		Whites		Blacks	
Node 1	Node 2	Model	Data	Model	Data	Model	Data	Model	Data
AP STEM	No college	0.52	0.48	0.37	0.50	0.51	0.51	0.17	0.15
AP STEM	Some college	3.92	3.98	4.78	5.05	4.52	4.64	2.92	1.53
AP STEM	STEM, low	1.23	1.67	2.33	2.01	2.03	2.00	0.48	0.37
AP STEM	STEM, high	1.94	1.98	3.80	3.30	3.09	2.83	0.60	0.53
AP STEM	NON-STEM, low	7.82	8.43	4.40	4.45	7.31	7.07	2.00	1.86
AP STEM	NON-STEM, high	5.76	5.31	4.65	6.03	5.95	6.21	1.68	1.20
AP NON-STEM	No college	0.36	0.33	0.25	0.19	0.30	0.26	0.23	0.26
AP NON-STEM	Some college	4.01	4.24	3.24	3.46	3.45	3.86	4.07	2.26
AP NON-STEM	STEM, low	0.44	0.69	0.52	0.61	0.51	0.68	0.34	0.22
AP NON-STEM	STEM, high	0.36	0.61	0.44	0.80	0.42	0.74	0.23	0.25
AP NON-STEM	NON-STEM, low	5.35	5.09	2.25	2.33	4.35	3.80	1.85	1.69
AP NON-STEM	NON-STEM, high	2.56	1.95	1.38	1.69	2.13	1.90	1.49	0.66
CTE STEM	No college	2.42	4.11	7.61	4.80	4.19	4.29	7.49	7.62
CTE STEM	Some college	14.31	15.65	24.60	20.14	17.14	16.76	27.24	25.00
CTE STEM	STEM, low q	0.35	0.66	1.51	0.84	0.98	0.81	0.54	0.20
CTE STEM	STEM, high q	0.23	0.27	0.60	0.49	0.39	0.40	0.33	0.07
CTE STEM	NON-STEM, low	5.96	7.60	6.01	6.26	6.48	7.40	4.54	3.31
CTE STEM	NON-STEM, high	1.49	1.51	1.67	1.95	1.59	1.80	1.28	0.51
CTE NON-STEM	No college	3.56	3.71	3.84	2.89	3.24	3.21	5.35	5.69
CTE NON-STEM	Some college	16.87	14.87	11.99	13.92	13.74	13.63	19.85	19.19
CTE NON-STEM	STEM, low q	0.48	0.65	0.61	0.65	0.61	0.68	0.33	0.19
CTE NON-STEM	STEM, high q	0.22	0.25	0.23	0.37	0.22	0.31	0.11	0.09
CTE NON-STEM	NON-STEM, low	8.59	7.65	3.97	4.87	7.27	6.42	3.37	3.04
CTE NON-STEM	NON-STEM, high	1.70	1.45	1.15	1.49	1.56	1.49	0.93	0.50
None	No college	1.26	0.85	1.64	1.32	1.10	1.09	2.87	1.90
None	Some college	4.55	3.30	3.96	5.60	3.70	4.09	7.54	6.14
None	STEM, low q	0.25	0.20	0.29	0.33	0.28	0.27	0.26	0.09
None	STEM, high q	0.14	0.14	0.18	0.31	0.16	0.22	0.13	0.09
None	NON-STEM, low	2.53	1.84	1.29	1.87	2.16	1.94	1.18	0.99
None	NON-STEM, high	0.83	0.52	0.43	0.83	0.63	0.69	0.59	0.28