INFORMATION CAPITAL AND EARLY-CAREER WAGES

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Job-Market Paper

Abstract: Traditional human capital theory posits that the larger the stock of a worker's human capital, the more productive the worker will be and the more the worker will earn. Information capital, the knowledge that individuals possess about the labor market and about their aptitudes and tastes for different levels of education and types of employment, is another component of an individual's skill set that affects productivity and wages. In this paper, I define one measure of information capital: labor-market knowledge captured by 12th graders' understanding of the educational requirements of the jobs they hope to hold at age 30. I demonstrate that inaccurate labor-market information affects wages through decreased job tenure, driven by individuals entering and leaving postsecondary school as they come to an accurate understanding of the educational requirements of their chosen jobs. I find that poor labor-market knowledge affects workers well into their twenties: despite having higher grades and test scores, workers who were mistaken about educational requirements in high school earn wages no higher than workers in similar jobs who were not. I also investigate the role of high school guidance counselors and vocational education faculty in students' information-capital acquisition, and show that schools can influence students' career aspirations and labor-market knowledge.

JEL Codes: J24, J31, I21

* I thank Julie Cullen, Nora Gordon, Julian Betts, Gordon Dahl, Kate Antonovics, and Prashant Bharadwaj for their invaluable advice and incisive suggestions.

I. Introduction

Traditional human capital theory posits that the larger the stock of a worker's human capital, the more productive the worker will be and the more the worker will earn. Human capital refers to the skills and knowledge an individual acquires through education and experience, as well as the individual's innate abilities and values. The theory distinguishes between general and specific human capital. To this list should be added information capital: the knowledge that workers possess about the labor market and about their aptitudes and tastes for different levels of education and types of employment. Information capital is another component of an individual's skill set that affects productivity and wages.

In this paper, I define one measure of information capital: labor-market knowledge captured by 12th graders' understanding of the educational requirements of the jobs they hope to hold at age 30. I demonstrate that inaccurate labor-market information affects wages through decreased job tenure, driven by individuals entering and leaving postsecondary school as they come to an accurate understanding of the educational requirements of the jobs they wish to hold. I find that poor labor-market knowledge affects workers well into their twenties: despite having higher grades and test scores, workers who were mistaken about educational requirements in high school earn wages no higher than workers in similar jobs who were not. I also investigate the role of high school guidance counselors and vocational education faculty in students' information-capital acquisition, and show that schools can influence students' aspirations and labor-market knowledge.

This paper makes several contributions. First, I demonstrate the importance of information capital for both educational attainment and wages. Few studies have explored the effect of labor-market knowledge on educational attainment.[1] Ludwig (1999) focuses on inner-city youth and uses two measures of labor-market information: individuals' understanding of the job duties associated with nine different occupations and the difference between the average education level in a respondent's reported occupational goal and his or her reported educational aspirations. He finds that those with better information are more likely to graduate from high school. I extend this by documenting a link between labor-market information and postsecondary attainment.

A small body of literature examines the relationship between wages and information capital as measured by an individual's score on the Knowledge of World of Work (KWW) test and wages. KWW measures respondents' knowledge of the labor market by asking them about the duties, educational requirements, and relative earnings of ten occupations. Blackburn and Neumark (1992) find that labor-market knowledge does not explain inter-industry and inter-occupation wage differentials, but Polachek and Robst (1999) conclude that workers with better labor-market knowledge earn a larger proportion of their potential wages. I focus on labor-market knowledge relevant to the jobs students wish to hold and the effect of this labor-market knowledge on wages early in the individuals' careers.

Another contribution is to show that one channel through which inaccurate labor-market information affects wages is decreased job tenure. Farber (1999) investigates the

[1] A more substantial and currently quite active body of literature addresses the role of perceived returns to education in determining educational outcomes. See Manski (1989), Kaufmann and Attanasio (2009), Jensen (forthcoming, 2010), and Nguyen (2008).

roles of firm-specific capital and worker heterogeneity in mobility rates in explaining the following facts concerning job tenure in the United States: long-term employment relationships are common, most new jobs end early, and the probability of a job ending declines with tenure. I provide evidence that one facet of worker heterogeneity, poor labor-market information, is negatively related to job tenure early in workers' careers.

The other contributions of this paper are to present information capital as a novel output of an education production function and to provide preliminary evidence suggesting that schools can influence information-capital acquisition. An extensive body of literature considers measures of human capital such as student achievement as outputs produced by school inputs such as class size and teacher quality. Though a positive relationship between school resources and student achievement has been documented,[2] the debate over how specific school inputs affect achievement continues.[3] I consider the relationship between information capital and school inputs aimed directly at influencing students' career aspirations and labor-market knowledge—guidance counselors and vocational education faculty.

This paper proceeds as follows. Section II lays out the framework of this study and describes the predictions about the effects of information capital on wages via educational attainment and job tenure. Section III describes the empirical methodology. Section IV describes the primary data source and the student- and school-level variables used throughout the analysis. Section V contains the results of regressions measuring the effect of labor-market knowledge on wages and discusses the role of job tenure and

[2] See, for example, Card and Payne (2002) or Rivkin, Hanushek, and Kain (2005).
[3] Alan Krueger and Erik Hanushek debate the effect of class size on student achievement in Mishel and Rothstein, eds. (2002); Rivkin, Hanushek, and Kain (2005) discuss the effects of teachers on reading and math achievement.

educational attainment. In Section VI, I analyze the relationship between information capital and school inputs such as guidance counselors and vocational faculty. Section VII concludes.

II. Framework and Predictions

II.A.Four Labor-Market-Knowledge Types

Educational attainment and wages are tied to students' career aspirations and their understanding of the educational requirements of their chosen careers. My measure of information capital comprises two components: a student's professional aspirations and her understanding of the educational requirements of her chosen job.

I classify jobs into two types: "college jobs" require individuals to hold a four-year college degree; "noncollege jobs" do not. In this simple framework, only those who graduate from a four-year institution can hold college jobs; anyone can hold a noncollege job.

In 12^{th} grade, students state their professional aspirations—college job or noncollege job—without necessarily understanding the job's educational requirements. At this time, they also declare how much education they believe is required for the job they wish to hold: a four-year college degree, or less than a college degree.

Combining these two dichotomous measures gives rise to four types of students. Students who are "not on the college track" aspire to a noncollege job and correctly believe that a college degree is not required for this job—their path to a noncollege job is straightforward. Students "on the college track," on the other hand, aspire to a college job and correctly believe that a college degree is required—their path to a college job is straightforward.

Students who overestimate the educational requirements of jobs aspire to a noncollege job but believe that a college degree is required. These “overestimators” have inaccurate labor-market information since their career goals and understanding of educational requirements do not line up, but these students do not close any doors for themselves by thinking college is required when it is not—college graduates can still hold noncollege jobs. Their job path, however, is not straightforward.

Students who underestimate educational requirements aspire to a college job but believe that a college degree is not required. In this simple framework, holding a college job without a college degree is impossible—the misalignment of these students’ career goals and perceived educational requirements precludes them from attaining their chosen jobs. Unlike overestimators, “underestimators” face a barrier to achieving their professional goals. Like overestimators, their job path is not straightforward.

In the next subsection, I outline how to overcome one form of omitted variable bias in order to isolate the causal effect of poor labor-market knowledge on wages.

II.B. Positive Omitted Variable Bias and the Effect of Poor Labor-Market Knowledge

Suppose wages can be predicted according to the following reduced-form model:

$$y_i = X_i\beta + M_i\gamma + \alpha_i + \varepsilon_i, \quad (1)$$

y_i is log hourly wages for individual *i*, X_i represents observable characteristics that affect wages such as ability, motivation, family background, and risk and rate-of-time preferences M_i is a dummy variable indicating that *i* is misinformed; that is, that *i* is either an overestimator or an underestimator. α_i represents unobservable characteristics, and ε_i is a mean-zero error.

Let $\bar{M}_1 = E\left(M_i \mid X_i, i \text{ is not on the college track}\right)$, $\bar{M}_2 = E\left(M_i \mid X_i, i \text{ is an overestimator}\right)$, $\bar{M}_3 = E\left(M_i \mid X_i, i \text{ is an underestimator}\right)$, and $\bar{M}_4 = E\left(M_i \mid X_i, i \text{ is on the college track}\right)$. $\bar{M}_1 = \bar{M}_4 = 0$ because these types have accurate information, and $\bar{M}_2 = \bar{M}_3 = 1$ since these types are misinformed. Now, let $\Delta\bar{M}_{2-1} = \bar{M}_2 - \bar{M}_1$, and $\Delta\bar{M}_{3-1} = \bar{M}_3 - \bar{M}_1$. Note that $\Delta\bar{M}_{2-1} = \Delta\bar{M}_{3-1} = 1$. Thus, γ can be interpreted as the effect of being misinformed.

In addition, let $\bar{\alpha}_1 = E\left(\alpha_i \mid X_i, i \text{ is not on the college track}\right)$, $\bar{\alpha}_2 = E\left(\alpha_i \mid X_i, i \text{ is an overestimator}\right)$, $\bar{\alpha}_3 = E\left(\alpha_i \mid X_i, i \text{ is an underestimator}\right)$, and $\bar{\alpha}_4 = E\left(\alpha_i \mid X_i, i \text{ is on the college track}\right)$. Finally, $\Delta\bar{\alpha}_{2-1} = \bar{\alpha}_2 - \bar{\alpha}_1$, and $\Delta\bar{\alpha}_{3-1} = \bar{\alpha}_3 - \bar{\alpha}_1$. $\Delta\bar{\alpha}_{2-1}$ and $\Delta\bar{\alpha}_{3-1}$ represent omitted-variable bias.

I will isolate the causal effect of labor-market knowledge by comparing outcomes across types. The expected difference in outcomes between group *j* and group *k* is given by

$$E\left(\Delta y_{j-k} \mid X\right) = \Delta\bar{M}_{j-k}\gamma + \Delta\bar{\alpha}_{j-k}. \tag{2}$$

First, consider the comparison between overestimators (Type 2) and noncollege-track students (Type 1). These students share a career aspiration—neither type wants a college job—but the overestimators incorrectly believe that college is necessary. The expected difference in outcomes, given the *X* variables which are common to all types, is given by

$$E\left(\Delta y_{2-1} \mid X\right) = \Delta\bar{M}_{2-1}\gamma + \Delta\bar{\alpha}_{2-1} = \gamma + \Delta\bar{\alpha}_{2-1} \tag{3}$$

In Section IV, I show that students who believe that overestimators are higher-achieving and of higher socioeconomic status (SES) than noncollege-track students. Since it is likely that overestimators are positively selected on unobservables as well, $\Delta\bar{\alpha}_{2-1}$ should be positive.

My hypothesis is that γ is negative. Though overestimators are not closing any doors for themselves with their lack of understanding of the educational requirements of their chosen jobs, they do possess inaccurate labor-market information. Controlling for observable differences, if I find that overestimators have wages no greater than those of noncollege-track students, then inaccurate labor-market information outweighs any positive selection and I can conclude that poor labor-market information has a negative effect on wages.

Now, consider the comparison between underestimators and noncollege-track students. The expected difference in outcomes is

$$E\left(\Delta y_{3-1} \mid X\right) = \Delta\bar{M}_{3-1}\gamma + \Delta\bar{\alpha}_{3-1} = \gamma + \Delta\bar{\alpha}_{3-1} \tag{4}$$

Neither of these thinks that a college degree is necessary, but underestimators are incorrect in this belief since they want a college job. In Section IV, I show that underestimators have higher grades and test scores than noncollege-track students. Thus $\Delta\bar{\alpha}_{3-1}$ is likely to be positive—underestimators are likely to be positively selected on unobservables as well as observables.

I hypothesize that γ is negative since underestimators have inaccurate labor-market information. Controlling for observables, if I find that underestimators earn wages no greater than noncollege-track students, I can again conclude that the negative effect of inaccurate labor-market information outweighs any positive omitted variable bias.

The other possible comparisons do not allow me to draw meaningful conclusions about the effect of inaccurate labor-market knowledge on wages. Both noncollege- and college-track students have accurate labor-market information (i.e., $\Delta\bar{M}_{4-1} = 0 - 0 = 0$), and both overestimators and underestimators have inaccurate labor-market information (i.e., $\Delta\bar{M}_{3-2} = 1 - 1 = 0$). Comparing college-track students to underestimators or to overestimators, the omitted variables bias works in the same direction as any positive effect of accurate information. That is, since college-track students are positively selected relative to over- and underestimators, $\Delta\bar{\alpha}_{4-2}$ and $\Delta\bar{\alpha}_{4-3}$ are positive, and since college-track students have accurate labor-market information, the γ s should be positive as well. Thus, finding that college-track students earn more than underestimators or overestimators tells us nothing about the effect of accurate labor-market knowledge since the positive omitted variables bias reinforces any positive effect of accurate information.

In the next subsection, I discuss possible mechanisms through which poor labor-market information affects wages.

II.C. How Does Poor Labor-Market Information Affect Wages? The Role of Educational Attainment and Job Tenure

In the framework I outline in this section, I focus on a subset of causal mechanisms through which inaccurate information affects wages. I show that inaccurate information can lead to decreased job tenure because of time spent in nonproductive education. That is, over- and underestimators make more missteps by entering and leaving postsecondary school as they come to an accurate understanding of the educational requirements of the jobs they wish to hold. This framework does not consider the very real possibility that more education could lead to more job tenure and higher wages due to returns to some college and/or differential exposure to unemployment. The predictions that this framework yields only apply if the negative effect of missteps dominates any positive effects of education. In Section V, I show that the data do, in fact, bear out these predictions.

I will illustrate the possible job paths for students of each labor-market-knowledge type. Consider a simple, three-period example. Life does not end at $t = 3$, but wages will be measured at that time. Acquiring a college degree takes two periods—if a worker decides to (re-) join the labor force after attending college for only one period, that worker must work in the noncollege job. While in college, students earn 0. For new hires, the college job pays w^C and the noncollege job pays w^N, with $w^C > w^N$. This assumption is in line with the literature on the return to a college degree. For example, plotting age-earnings profiles using CPS data, Card (1999) shows that at zero years of experience, college-educated workers earn higher wages than high school graduates.

Altonji and Williams (2005) and others show that job tenure has a positive effect on wages. In my framework, wages rise with job tenure at a rate ρ per period. At $t = 0$, all students graduate from high school.

In this simple framework, once an individual's job choice and educational requirements are aligned, that individual does not switch jobs. In addition, immediately out of high school, individuals pursue a path dictated by their perceived educational requirements. Thus, students not on the college track head straight for the noncollege job and do not switch, and students on the college track head straight for the college job via college. Overestimators and underestimators, however, face circuitous paths to their chosen jobs. While in practice, all groups will be learning about their preferences for jobs and education, misinformed individuals have more to learn about the constraints they may face in attaining their chosen jobs. Thus the relative rates of missteps should match the predictions in this section.

Figure 1 illustrates all possible career paths and gives the wages earned by each type of worker in each time period. Students on the noncollege track work for three periods. At the end of the third period, these students earn $w^N(1+\rho)^3$. Students on the college track attend college for two periods and work in the college job for one period. At the end of three periods, these students earn $w^C(1+\rho)$.

Overestimators believe a college degree is required so they attend college immediately after graduating from high school. From here, their paths diverge. Some overestimators realize that a college degree is not required for the noncollege job, and join the labor force in the second period. They work for two periods and at the end of this time, earn $w^N(1+\rho)^2$. Some overestimators re-evaluate their career goals and decide they want a college job, finish college, and earn $w^C(1+\rho)$ in the last period.

Underestimators do not believe a college degree is required, so they work the period immediately after high school in the noncollege job, the only one open to them.[4] From there, they can follow one of three paths. Some re-evaluate their career goals and stick with the noncollege job. At the end of period three, these workers earn $w^N(1+\rho)^3$.

[4] To keep this framework as simple as possible while preserving its usefulness in understanding the roles of educational attainment and job tenure, I ignore the possibility of voluntary unemployment due to w^N being less than the individual's reservation wage.

Others realize that a college degree is required for the college job, and decide to go to school. After attending school for one year, some of these decide that schooling is too costly and return to the noncollege job. These workers earn $w^N(1+\rho)^2$ at the end of the last period. Finally, some underestimators stay in school for two periods. These earn 0 at the end of the third period.

This framework predicts that overestimators who end up on the noncollege job earn lower wages than noncollege-track individuals on the same job because they have accumulated less job tenure. They have lower job tenure because they spent some time in nonproductive education before re-evaluating their career plans, so I can also predict that overestimators—even those on the noncollege job—will have higher educational attainment than noncollege-track students.

Turning to the comparison between underestimators and noncollege-track students, noncollege-track students have accumulated at least as much job tenure in the noncollege job as underestimators, because some underestimators give college a try before returning to the noncollege job, and some stay in school. Thus, the framework in this section predicts that, on average, underestimators will earn wages less than or equal to the wages of students not on the college track but will have (weakly) more educational attainment and (weakly) less job tenure.

Section III describes the empirical methodology I use to test these predictions.

III. Empirical Methodology

In this section, I describe the empirical models I employ in order to measure the effect of labor-market knowledge on wages and test the predictions from Section II. First, I compare overestimators to noncollege-track students. These students share a job aspiration in 12th grade—both want a noncollege job. Section II predicts that overestimators who end up in the noncollege job will earn lower wages than noncollege-track students in the same job, and have higher educational attainment and lower job tenure. Thus I restrict the sample to individuals who desired a noncollege job in 12th grade and ended up at a noncollege job in their mid-twenties. (I will describe this method of job classification in more detail in Section V). I estimate the following:

$$y_{is} = \alpha + \beta_2 T_{2is} + \lambda X_{is} + \delta_s + \varepsilon_{is}, \tag{5}$$

where y_{is} is the outcome of interest for student *i* at school *s*—log hourly wage, educational attainment, or job tenure. T_{2is} is a dummy denoting a student who does not want a college job but thinks the job requires a college degree—an overestimator. (Since I restrict the sample to those students not desiring a college job in 12th grade, T_{1is} —denoting noncollege-track students—is the omitted category).

Next, I compare underestimators to noncollege-track students. These share a belief that a college degree is not required for their chosen jobs. Section II predicts that underestimators will earn (weakly) lower wages than noncollege-track students, have (weakly) more educational attainment, and have (weakly) lower job tenure. This prediction does not depend on the type of job the individuals hold in their mid-twenties. I restrict the sample to the two types of interest and estimate

$$y_{is} = \alpha + \beta_3 T_{3is} + \lambda X_{is} + \delta_s + \varepsilon_{is}, \tag{6}$$

where y_{is} defined as in (5), and T_{3is} denotes underestimators, with noncollege-track students as the omitted category. In both (5) and (6), X_{is} is a vector of student characteristics.

I am interested in the causal interpretation of β_2 and β_3, which tell me the effect of being an overestimator and an underestimator, respectively, on the outcome of interest, relative to noncollege-track students. Here, it is important to note that focusing on comparisons between over- or underestimators and noncollege-track individuals allows me to isolate the causal effect of poor labor-market knowledge on wages because the negative misinformation effect moves in the opposite direction of the positive omitted variable bias. To the extent, however, that educational attainment is positively associated with any omitted variables, and in turn is negatively associated with job tenure, I am not able to ascribe a causal interpretation to the βs in regressions with educational attainment and job tenure as outcomes.

In addition to the positive omitted variable bias described in Section II, another barrier to causal interpretation of the βs is the possibility that poor labor-market information is a proxy for variables such as "flakiness" or poor estimation ability that may negatively affect wages. In order to address this source of bias, I use several different specifications of the models in (5) and (6), adding more and more variables to X_{is} each time. In particular, I add variables measuring noncognitive traits and risk and rate-of-time preferences in order to ensure that my information-capital measure is not just a proxy for undesirable individual characteristics.

Unobserved school characteristics can also be a source of omitted variable bias. I address this source of bias by including school fixed effects, δ_s. Thus I am measuring within-school differences in wages as a function of information-capital type and student characteristics.

Because type is determined in high school, labor-market type coefficients are difficult to interpret if I include student-level measures also determined in high school. This is because high school performance and participation measures such as test scores, grades, and participation in extracurricular activities may be codetermined with information-capital type. For example, if I receive poor grades, I may decide that a college job is not for me. Conversely, if I decide a college job is not for me, I may put forth less effort in school and earn lower grades. Or, if I think college is required for my job, I may put forth more effort and earn higher grades, or decide to participate in extracurricular activities. Thus I exclude variables codetermined with information-capital type because they prevent meaningful interpretation of the β s in (5) and (6).

12^{th} grade standardized test scores, however, are arguably not codetermined with students' information-capital type. Because they are not observed by future employers or college admissions committees, scores on these tests depend less on students' motivation and career and educational aspirations than do grades and participation in extracurricular activities. In order to account for experiences in high school affecting postsecondary and labor-market outcomes through ability but not through career aspirations or labor-market knowledge, I include 12^{th} grade standardized test scores in one of the specifications in Section V.

Section IV contains a description of my primary data source and a detailed description of the variables used throughout the analysis.

IV. Data and Description of Variables

IV.A. Primary Data Source

My primary data source is the National Education Longitudinal Study of 1988 (NELS), a nationally representative sample of 27,805 eighth-grade students interviewed in 1988. Follow-ups took place in 1990 (when most were in 10th grade), 1992 (12th grade), 1994, and 2000 (when the respondents' average age was 26). The study contains data from detailed student, parent, and school administrator questionnaires, as well as high school transcript data and information on postsecondary and labor-market outcomes.

IV.B. Variables Used to Measure Labor-Market Knowledge

In order to measure labor-market knowledge, I classify students into types based on their answers to two 1992 survey questions. The first asks about job goals: "Which of the categories below comes closest to describing the job or occupation that you expect or plan to have … when you are 30 years old?" I classify jobs into college and noncollege jobs by mapping detailed occupations from the March 1992 CPS to the jobs listed in the 1992 NELS survey. (Please see Appendix A for this mapping).[5] If at least 60 percent of the individuals in a job have a bachelor's degree or more according to the CPS, I classify that job as a college job. Table 1 contains these job classifications.

As the other component of my labor-market knowledge measure, I consider students' responses to the question, "How much education do you think you need to get the job you expect or plan to have when you are 30 years old?" which immediately follows the question on career aspirations in the 1992 NELS survey. If students answer "4 or 5 year college degree" or more, I classify them as perceiving that their chosen job requires a college degree.

[5] All appendices are available at http://econ.ucsd.edu/~jlthomas/info_capital_appendices.

Combining the answers to these two questions, I construct a measure of labor-market knowledge that can take four values. Table 2 shows that 23.8 percent of the respondents are not on the college track, 22.0 percent are overestimators, 5.5 percent are underestimators, and 48.7 percent are on the college track.[6]

A potential criticism of this binary classification of jobs is that I may have misclassified a number of students. For example, I classify Bill, a student who says he wants to be a "Professional (e.g., accountant, registered nurse, engineer)" but who does not plan on graduating from college, as an underestimator. Bill may, in fact, plan to be a registered nurse and attain this goal by attending two years of nursing school after high school. Thus he has correctly estimated the educational requirements of his chosen job, and should be classified as a student not on the college track rather than an underestimator.

In order to address this criticism, I have repeated the analysis in Section V with continuous measures of labor-market knowledge which I briefly describe here. Instead of assigning each student to a type, I assign each student a probability of being in each type as follows. First, define

$$c_i = \begin{cases} 0 \text{ if student } i \text{ thinks a college degree is not required} \\ 1 \text{ if student } i \text{ thinks a college degree is required} \end{cases}. \qquad (7)$$

Then, let p_i be the percent of individuals in the U.S. in student *i*'s chosen job with a B.A. or more (taken from the March 1992 CPS). Now, the probability of being in each type is given by

[6] 15,511 students have nonmissing observations for this measure.

$$\begin{aligned}
&\Pr\left(\text{Noncollege track}\right)_i = \left(1-c_i\right)\left(1-p_i\right) \\
&\Pr\left(\text{Overestimator}\right)_i = c_i\left(1-p_i\right) \\
&\Pr\left(\text{Underestimator}\right)_i = \left(1-c_i\right)\left(p_i\right) \\
&\Pr\left(\text{College track}\right)_i = c_i p_i
\end{aligned} \quad . \tag{8}$$

For example, instead of being unequivocally placed into category 3 as an underestimator, Bill (from the example above) would receive the following values:

$$\begin{aligned}
&\Pr\left(\text{Noncollege track}\right)_{Bill} = 1\left(1-0.66\right) = 0.34 \\
&\Pr\left(\text{Overestimator}\right)_{Bill} = 0\left(1-0.66\right) = 0 \\
&\Pr\left(\text{Underestimator}\right)_{Bill} = 1\left(0.66\right) = 0.66 \\
&\Pr\left(\text{College track}\right)_{Bill} = 0\left(0.66\right) = 0
\end{aligned} \quad . \tag{9}$$

Since 66 percent of individuals in the "Professional (e.g., accountant, registered nurse, engineer)" category have a college degree according to the CPS, and since Bill does not think college is required for his job, he has a 34 percent chance of being correct and a 66 percent chance of being incorrect. In other words, he has a 34 percent chance of being a student not on the college track with accurate labor-market knowledge, and a 66 percent chance of being an underestimator.

Since my results in Section V are not sensitive to using these continuous measures (see Appendix B for the continuous results), I choose to describe and report results for the discrete measure because it is consistent with my framework in Section II and because it lends itself to more natural discussion and interpretation.

IV.C. Description of Student- and School-Level Variables

Recall from (5) and (6) that I regress the outcome of interest on labor-market knowledge dummies and student characteristics. In order to show that my information capital measure is not a proxy for unobserved abilities or skills, I use several different specifications of the models in (5) and (6), adding successively more covariates from one to the next. I do this by partitioning X, the vector of student characteristics, into four different groups of variables: $X1$, $X2$, $X3$, and $X4$.

$X1$ contains the following eighth-grade academic ability, achievement, and coursetaking measures: a reading and math standardized test score composite, GPA, reading, math, and science proficiency measures, a dummy variable indicating whether a student was held back in a grade prior to eighth, and a dummy variable indicating that the student took algebra in eighth grade. According to the 2008 Brown Center Report on American Education, during the 1990s and the 2000s, the percentage of American eighth graders taking algebra has nearly doubled. The impetus for this increase came during the Clinton Administration which made universal eighth grade algebra a national goal in order to enable students to succeed in higher-level math courses in high school. Thus, taking algebra in eighth grade is an important predictor of academic orientation and readiness for more advanced high school math courses.[7]

$X1$ also contains two noncognitive or personality-trait measures: locus of control and self-concept. These measures have begun to receive attention in the economics literature as important influences on schooling decisions and wages (see, for example, Heckman, Stixrud, and Urzua, 2006). Students' answers in the eighth-grade survey to six questions eliciting the degree to which they feel they can control what happens to them

[7] Though there is some evidence that students who take algebra in eighth grade outperform other students, recent research calls into question the value of eighth grade algebra for under-prepared students (2008 Brown Center Report on American Education). It is also important to note that offering eighth-grade algebra reflects a school's resources, not just an individual student's academic orientation or high-school readiness.

are used to construct the locus of control score.[8] The higher the score, the more the student feels he can control events. Answers to seven questions on students' feelings of worthiness or self-esteem are used to construct the self-concept score,[9] with a higher score indicating more self-esteem.

$X2$ contains basic student and family characteristics: age, gender, race and ethnicity, and family SES. Family SES is a composite of father's and/or mother's education level, father's and/or mother's occupation, and family income.

$X3$ contains variables measuring students' household environments and risk and rate-of-time preferences: dummies indicating that a student's home language is non-English only/non-English dominant, that the student lived in a single-parent household in eighth grade, that the student often discussed his or her studies with parents in eighth grade, and that the student smoked in eighth grade. I include the smoking dummy to capture risk and time preferences, since smoking has been linked to both high discount rates and low levels of risk aversion; see, for example, Fersterer and Winter-Ebmer (2003) and Ida and Goto (2009). $X4$ contains just one variable: a 12th grade reading and math standardized test score composite.

In Section V, I use five different specifications of (5) and (6). The first contains the relevant information-capital dummy and school fixed effects as the only right-hand-

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[8] Students respond to the following statements by choosing from a four-point Likert Scale (strongly agree, agree, disagree, strongly disagree): "I don't have enough control over the direction my life is taking," "In my life, good luck is more important than hard work for success," "Every tine I try to get ahead, something or somebody stops me," "My plans hardly ever work out, so planning only makes me unhappy," "When I make plans, I am almost certain I can make them work," and "Chance and luck are very important for what happens in my life."

[9] The self-concept statements are as follows: "I feel good about myself," "I feel I am a person of worth, the equal of other people," "I am able to do things as well as most other people," "On the whole, I am satisfied with myself," "I certainly feel useless at times," "At times, I think I am no good at all," and "I feel I do not have much to be proud of."

side variables. Specification (2) includes these as well as $X1$, specification (3) adds $X2$, specification (4) adds $X3$, and specification (5) adds $X4$.

The school-level variables I analyze in Section VI are the number of guidance counselors in student *i*'s school divided by tenth grade enrollment in the school, the number of vocational education faculty divided by tenth grade enrollment,[10] whether the school is a vocational school, the number of AP courses offered, the percent of the previous year's graduates attending 2- and 4-year schools, tenth grade enrollment, student-teacher ratio, percent non-White, percent receiving free or reduced-price lunch, dummies for urban, suburban, or rural location, and regional dummies (Northeast, North Central, South, and West).[11]

Table 3 contains the means of each of these variables by labor-market-knowledge type. In terms of eighth-grade GPA, reading, math, and science proficiency, and eighth- and 12th-grade standardized test scores, students on the college track are the highest achieving, followed by overestimators, then underestimators, and finally, students not on the college track. The same pattern holds for SES, though the difference between underestimators and noncollege-track students is not statistically significant. Considering the predictions on wages, it is interesting to note that both underestimators and overestimators are higher-achieving than noncollege-track students, and in addition, overestimators are of significantly higher SES, even though these two types are predicted to have wages no greater than the noncollege-track students (at least on the noncollege job).

[10] The tenth-grade (1990) NELS survey reports the number of guidance counselors and vocational education faculty as categorical variables with 1 = none, 2 = 1-5, 3 = 6-10, 4 = 11-15, and 5 = over 15. I assign the value 0 to category 1, 3 to category 2, 8 to category 3, 13 to category 4, and 15 to category 5.

[11] Because the school administrator surveys from students' tenth grade year had much higher response rates than the 12th grade surveys, I use tenth grade school-level measures.

Table 3 also shows the importance of using school fixed effects to estimate the effect of information-capital type on wages. As measured by variables such as the percent of the previous year's graduates attending four-year colleges and student-teacher ratio, college-track students and overestimators appear to attend schools that have more resources and are more academically oriented than schools attended by noncollege-track students and underestimators. If schools differ on unobservable characteristics as well, merely including these school-level variables as covariates in the wage regressions will not eliminate omitted variable bias. For this reason, I include school fixed effects in the regressions discussed in the next section.

V. The Effect of Labor-Market Knowledge on Wages

In this section, I demonstrate that poor labor-market knowledge has a negative effect on wages, and this effect appears to operate through educational attainment and job tenure as outlined in Section II. First, since some of the predictions from Section II depend on the job an individual holds in her mid-twenties, I show that information-capital type is an important predictor of job type. I then present the results on wages, job tenure, and educational attainment. In the tables in this section, I report only the coefficients on the information-capital dummies. Appendix C contains full regression results.

V.A. Do Individuals End Up in Their Chosen Jobs?

In this subsection, I analyze whether information-capital type predicts holding a college job in one's mid-twenties. I first classify the jobs that employed respondents report in the 2000 survey as college or noncollege jobs. Recall that, in order to classify 12^{th} grade job aspirations, I map detailed occupations from the March 1992 CPS to the jobs listed in the 1992 survey, classifying as a "college job" one in which at least 60 percent of individuals have a bachelor's degree or more. I use the same method to classify the respondents' jobs as of 2000, but the job categories given in the 2000 survey are much harder to link to CPS job categories. Thus I also calculate the percent of individuals within each job with a B.A. or above according to the 2000 NELS survey. If I use a 55 percent cutoff with the latter method, discrepancies between the two methods are minimized. Appendix A contains these mappings.

Table 4 contains these results. I use the same methodology discussed in Section III, equations (5) and (6), except I include the full set of information-capital dummies: T_1 denotes noncollege-track students, T_2 denotes overestimators, T_3 denotes underestimators. T_4, college-track students, is the omitted category. The dependent variable is a dummy that equals one if the individual holds a college job in 2000. Linear probability results are reported; probit results show the same signs and significance levels.

Table 4 reveals that students on the college track in 12th grade are the most likely to hold a college job in their mid-twenties, followed by overestimators. According to unreported F-tests, overestimators are significantly more likely to hold a college job than noncollege-track students in all of the specifications. Though point estimates suggest that overestimators are more likely than underestimators to hold a college job, coefficients are not significantly different in specifications (3) through (5). Underestimators are no more or less likely to hold a college job than noncollege-track students—the coefficients on Type 3 and Type 1 are not significantly different in any of the specifications.

V.B. Results Pertaining to Wages

Now that I have demonstrated that information-capital type is an important predictor of the job an individual will hold in his mid-twenties, I now analyze its effect on wages. Table 5 compares overestimators to noncollege-track students, as in equation (5). The dependent variable is log hourly wage in 2000, when the average age of respondents is 26. OLS results are reported. I restrict the sample to students who aspired to a noncollege job in 12th grade and who were employed in a noncollege job in 2000. When no controls are included, overestimators appear to have higher wages than noncollege-track students—this is consistent with my statements in Section II that overestimators are positively selected relative to noncollege-track students on both observables and unobservables.

Once controls are added, point estimates are consistent with the predictions of Section II: overestimators earn lower wages than noncollege-track individuals on the noncollege job. This difference is not significant at conventional levels in specifications (2) through (4), but it has economic significance. Relative to students who had the same career aspirations and an accurate understanding of educational requirements in high school, individuals who overestimated educational requirements earn approximately 70 cents less per hour, translating to an annual income difference of approximately $1400.[12]

Table 6 contains the results from the comparison between underestimators and noncollege-track students.[13] Point estimates accord with the predictions in Section II:

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[12] If I do not condition on job type in 2000, the coefficient on the overestimator dummy is positive but very close to zero, and not significant. This coefficient suggests an hourly difference in wages of approximately three cents, and an annual difference of about $58. Even though a sizeable percentage of overestimators go to college and end up on a college job, overall they earn wages virtually indistinguishable from those earned by noncollege-track students, few of whom end up going to college and holding college jobs.

[13] Recall that, for this comparison, the framework in Section II does not require me to condition on type of job in 2000: as of period 3, all underestimators are either on the college job or in college. If I do condition on holding a noncollege job in 2000, results are qualitatively similar.

underestimators earn wages no higher than noncollege-track students, though the coefficient on the Type 3 dummy is not significantly different from zero in specifications (3) and (4). The lack of statistical significance belies the economic significance of this difference. Underestimators can be expected to earn approximately $1.50 per hour less than students not on the college track, an annual difference of approximately $3000.

I do not include a correction term to control for nonrandom selection into the labor force in the regressions reported in Tables 5 and 6. This is because information-capital type is not a significant predictor of being employed in 2000. I run the same set of regressions as in Tables 5 and 6 with a dummy indicating that the respondent was employed in 2000 as the dependent variable (of course, in comparing overestimators to noncollege-track students, I do not condition on the type of job in 2000). Point estimates are positive in all specifications for the coefficient on overestimators, and for underestimators in specifications (3) through (5)—indicating that, if anything, both types are more likely to be employed than students not on the college track. The coefficient on overestimators is not significantly different from zero in specifications (2) through (5), and the coefficient on underestimators is not significantly different from zero in any of the specifications. (Please see Appendix C for these results).

V.C. The Role of Job Tenure and Educational Attainment

According to the framework outlined in Section II, overestimators earn lower wages than noncollege-track individuals in the noncollege job because they have accumulated less job tenure. Table 7, reporting results from linear regressions of job tenure, measured in years, on the covariates discussed in Section IV, shows that overestimators have less job tenure than noncollege-track students conditional on holding a noncollege job in 2000. Point estimates range from -0.4 to -0.6 and are significant at less than the ten percent level in all specifications, indicating that overestimators have worked on the noncollege job for approximately 5-7 fewer months than noncollege-track students.[14]

Table 8 contains the results on educational attainment, comparing overestimators to noncollege-track students, conditional on holding a noncollege job in 2000. Educational attainment is a categorical variable taking values from one through seven (1: less than high school, 2: high school graduate, 3: some postsecondary but no degree or certificate, 4: certificate, 5: associate's degree, 6: bachelor's degree, 7: graduate degree). OLS results are reported; ordered probit results are qualitatively similar. The results accord with the predictions of Section II—overestimators have significantly greater educational attainment than noncollege-track students. Point estimates range from 0.5 to 1 and are significant at the less-than-one-percent level in every specification.[15]

Now I turn to the comparison between underestimators and noncollege-track students. Table 9 contains the results on job tenure. Recall that underestimators are predicted to have lower job tenure even without conditioning on job type. For the most part, point estimates accord with predictions. They range from -0.4 in specification (1) (5 fewer months) to 0.1 in specification (5) (1 more month).[16] Coefficients are not significantly different from zero in specifications (2) through (5). These results are difficult to interpret meaningfully, however, because unreported F-tests of the joint

[14] The difference in job tenure between overestimators and noncollege-track students is even more pronounced when I do not condition on job type in 2000.
[15] The difference in educational attainment between overestimators and noncollege-track students is even more pronounced when I do not condition on job type in 2000.
[16] This pattern holds if I do condition on holding a noncollege job, though when I do so, the point estimate remains negative in specification (5).

significance of all covariates yield p-values greater than 0.1 in specifications (2) through (5).

Table 10 contains the results comparing the educational attainment of underestimators to that of noncollege-track students. Underestimators have significantly greater educational attainment than noncollege-track students: point estimates range from 0.3 to 0.5 and are significant at the five percent level in each specification. These results lend support to the claim that underestimators earn wages no greater than those of noncollege-track students because some have given postsecondary education a try before returning to the noncollege job.

In this section, I have demonstrated that labor-market knowledge affects wages and discussed the role of job tenure and educational achievement. In the next section, I analyze school inputs that are associated with students' information capital.

VI. School Inputs Influencing Students' Information Capital

In this section, I conduct an analysis of the school inputs that are associated with students' career aspirations and labor-market knowledge. I attempt to control for unobservable neighborhood characteristics by including a detailed set of variables describing local labor-market conditions. I obtain zip-code level data on occupation, education, income, and employment from the 1990 Census, Summary Tape File 3, and zip-code level data on industrial mix and number of business establishments from 1994 County Business Patterns (CBP) data. From the Integrated Postsecondary Education Data Center (IPEDS), I obtain the number of 2- and 4-year colleges within each high school's zip code.

Traditional education production function approaches seek to determine the effect of school inputs such as teachers, administrative methods, and pedagogical techniques (as well as school characteristics such as enrollment and grade span) on test scores (see Schwartz and Zabel, 2005, for an overview of education production functions). In this section, I perform a preliminary analysis of the relationship between school inputs and students' information-capital accumulation.

I am particularly interested in the role of guidance counselors and vocational education faculty.[17] Interaction with guidance counselors and experience in vocational education courses are directly linked to students' career aspirations and knowledge of the labor market. Crawford, Johnson, and Summers (1997) provide evidence that labor-market information provided by schools affects wages, finding that school-to-work interventions such as transmitting labor market information to students while in high school translate into higher earnings.

In order to isolate the effect of guidance and vocational faculty on students' information-capital acquisition, an ideal experiment would randomly assign students to otherwise identical schools with different numbers of vocational and guidance faculty. Since this is infeasible, one practical way to measure this effect would be to find an instrument for the number of guidance counseling and vocational education faculty employed in a school. In 1990, the Carl D. Perkins Vocational and Applied Technology Act passed, changing both the levels of federal funding for vocational education and the way these funds were allocated within states. In future work, I will investigate the effects of this act within states and determine the usefulness of changes in federal funding levels

[17] A more up-to-date term for "vocational education" is "career and technical education." To be consistent with the wording of the NELS surveys, however, I use the term "vocational education."

as an instrument for the number of guidance counselors and vocational faculty within a high school. One difficulty in using such an instrument in this analysis is timing: the students I study are in 12th grade during the 1991-1992 school year, when the changes mandated by the Perkins Act went into effect. In order to use these changes as an instrument for guidance and vocational faculty and to estimate their effect on information-capital acquisition, I would need data from a period after the changes went into effect.

Lacking such an instrument, I proceed with a correlational analysis of the relationship between the number of guidance counselors and vocational faculty and information capital. I use a multinomial logit model relating individual students' information-capital type to school inputs and other covariates. Students choose the type that yields maximum indirect utility:

$$U_{iT} = W_{iT} + \varepsilon_{iT}\,, \tag{10}$$

where T = 1, 2, 3, or 4 (types are defined as above), and ε_{iT} is i.i.d. Type 1 Extreme Value. Choice of type depends on student, school, and neighborhood characteristics:

$$W_{iT} = \alpha + \beta G_{iT} + \gamma V_{iT} + \varphi X_{iT} + \lambda S_{iT} + \tau Z_{iT} + \varepsilon_{iT}\,. \tag{11}$$

The choice probability, or the probability that student *i* chooses type *T*, is given by

$$P_{iT} = \frac{\exp\left(W_{iT}\right)}{\sum_{T=1}^{4}\exp\left(W_{iT}\right)}\,. \tag{12}$$

The parameters of this model are estimated using the method of maximum likelihood.

The right-hand-side variables in (11) are defined as follows. G_{iT} is the number of full-time guidance counselors in student *i*'s school, divided by tenth grade enrollment in the school. V_{iT} is similarly defined for full-time vocational education faculty.[18]

In addition to these variables of interest, I include a large number of control variables. X_{iT} contains the full set of student characteristics described in Section IV. S_{iT} contains the following high school characteristics: a dummy indicating that the school is a vocational school, the number of AP courses offered, the percent of the previous year's graduates attending 2- and 4-year colleges, tenth grade enrollment, student-teacher ratio, percent non-White, percent receiving free or reduced-price lunch, dummies for urban or rural location (with suburban as the omitted category), and regional dummies (North Central, South, and West, with Northeast as the omitted category).

Z_{iT} contains a wide variety of zip-code level local labor-market characteristics, and interactions with parental characteristics.[19] I obtain the following from the 1990 Census, Summary Tape File 3: percent of workers with a college job (which I interact with a dummy variable indicating that at least one of student *i*'s parents has a college job),[20] percent of those 25 and older with a B.A. or more (which I interact with a dummy indicating that at least one of student *i*'s parents has a B.A.), and per-capita income. I

[18] The tenth-grade (1990) NELS survey reports the number of guidance counselors and vocational education faculty as categorical variables with 1 = none, 2 = 1-5, 3 = 6-10, 4 = 11-15, and 5 = over 15. I assign the value 0 to category 1, 3 to category 2, 8 to category 3, 13 to category 4, and 15 to category 5.
[19] I am only able to link zip-code data to public high schools within the NELS. Of the 1,694 schools with nonmissing observations on the relevant variables, 1,404 are public.
[20] To obtain the zip code measure, I classify 1990 2-digit SOC codes into college and noncollege jobs: "Executive, administrative, and managerial occupations" and "Professional specialty occupations" are college jobs; all others are noncollege jobs. To classify parents' jobs as college or noncollege, I use the method described in Section IV.

also include two variables from 1994 County Business Patterns:[21] a measure of industry diversity within each zip code (computed by adding up the number of unique 2-digit SIC codes that appear in the zip code) and the total number of business establishments. My last two measures, the number of two-year and four-year colleges within the zip code, come from the Integrated Postsecondary Education Data System (IPEDS).

Table 11 contains the coefficients on the guidance and vocational faculty variables. Students not on the college track form the base outcome; standard errors are clustered at the school level. Appendix D contains the full set of results.

Table 11 gives mixed evidence on the role of guidance counselors and vocational education faculty. There appears to be no relationship between information-capital type and the number of guidance counselors. As for vocational faculty, on one hand, the table shows a negative relationship between the number of vocational faculty and the odds of choosing Type 2 over Type 1: the more vocational faculty, the less likely a student is to be an overestimator relative to being not on the college track. This is evidence that vocational education faculty can influence students' understanding of the labor market—recall that Type 2 students (overestimators) have inaccurate labor-market information, while Type 1 (noncollege-track) students share their career aspirations but have accurate labor-market information.

On the other hand, the table also suggests a negative relationship between the number of vocational education faculty and the odds of choosing Type 4 (college track) over Type 1 (noncollege track). A larger vocational education faculty might be a signal that the school has a less academic and more vocational orientation, even if it is not

[21] 1994 is the first year that zip-code level data are available in CBP.

explicitly a vocational school. Students may choose to attend a vocationally oriented school because they aspire to a noncollege job, which would bias estimates of the effect of vocational faculty on choice of information-capital type if these nonrandom attendance patterns are not addressed. In addition, students attending a vocationally oriented school may have accurate labor-market information but be less likely to aspire to a college job, either because the student has considered all postsecondary possibilities and decided that a noncollege job is the best fit, or because the student has not been exposed to college-job options. There is, in fact, a positive correlation between vocational faculty and percent of previous year's graduates attending 2-year colleges, and a negative correlation between vocational faculty and percent attending 4-year schools. Even with an extensive set of controls including these measures, I cannot claim to have included all relevant variables that affect choice of school, career aspirations, and labor-market knowledge. Additionally, though I find evidence that schools can manipulate students' career aspirations and labor-market knowledge, I cannot say that hiring more vocational faculty would be a welfare-enhancing option. Clearly, more research is needed in this area.

Apart from specification issues, it is not surprising that I have difficulty linking guidance and vocational faculty to students' information capital in light of a 2002 study by the Ferris State University Career Institute for Education and Workforce Development. This study found that more than half of the students surveyed felt that no high school personnel had been helpful in providing career or educational advice. Finding a more precise link between guidance counselors and vocational faculty and students' career aspirations and labor-market knowledge, and finding ways to strengthen this link, remain areas for further inquiry.

VII. Conclusions and Directions for Future Research

This paper defines one measure of information capital comprising students' career aspirations and their knowledge of the labor market: 12th graders' understanding of the educational requirements of the jobs they hope to hold at 30. I develop a simple framework describing how inaccurate labor-market information leads to lower wages through decreased job tenure, driven by students entering and leaving postsecondary school as they come to an accurate understanding of the educational requirements of their chosen jobs. I find that, in similar jobs in their mid-twenties, and despite having higher grades and test scores, workers who had inaccurate labor-market information in high school earn wages no higher than students who had an accurate understanding of educational requirements. In order to determine if this effect extends past workers' early careers, repeating this analysis in a dataset like the National Longitudinal Survey of Youth which contains information on students' educational and job aspirations in high school as well as records of labor-market outcomes throughout workers' careers, is an important next step.

I also analyze school inputs that influence information capital, paying particular attention to the role of guidance counselors and vocational education faculty. Though this is an area ripe for future research, I find preliminary evidence that schools can influence students' career aspirations and labor-market knowledge.

Information capital is both a novel output of an education production function and an important determinant of wages via educational attainment and job tenure. This paper is an early step in understanding the relationship between information capital and these outcomes, and in understanding what schools can do to improve the quality of students' information capital and prepare them for postsecondary and labor-market success.

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Figure 1: Information Capital and Career Paths

Type of worker	1 (Noncollege track)	2 (Overestimator)		3 (Underestimator)			4 (College track)
Period 1	$w^N(1+\rho)$	In college (earn 0)	In college (earn 0)	$w^N(1+\rho)$	$w^N(1+\rho)$	$w^N(1+\rho)$	In college (earn 0)
Period 2	$w^N(1+\rho)^2$	$w^N(1+\rho)$	In college (earn 0)	$w^N(1+\rho)^2$	In college (earn 0)	In college (earn 0)	In college (earn 0)
Period 3	$w^N(1+\rho)^3$	$w^N(1+\rho)^2$	$w^C(1+\rho)$	$w^N(1+\rho)^3$	$w^N(1+\rho)^2$	In college (earn 0)	$w^C(1+\rho)$

Table 1: College and Noncollege Jobs

CPS jobs: Percent with B.A.	*Career Goals in 12th Grade: Occupation at Age 30*	*Classify as "College Job"*	*Percent*
12.87%	Office worker	No	3.24%
5.89%	Tradesperson	No	2.53%
7.26%	Farmer, farm manager	No	0.86%
9.56%	Full-time homemaker[a]	No	1.06%
3.65%	Laborer	No	0.68%
44.30%	Manager (e.g., sales manager, office manager)	No	5.28%
10.17%	Military	No	2.44%
4.04%	Operator (of machines or tools)	No	0.98%
65.94%	Professional (e.g., accountant, registered nurse, engineer)	Yes	26.71%
86.07%	Professional (e.g., dentist, doctor, lawyer)	Yes	19.65%
31.76%	Owner of a small business or restaurant, contractor	No	5.97%
13.25%	Protective service	No	3.68%
22.58%	Sales	No	1.69%
81.17%	School teacher	Yes	7.27%
4.79%	Service worker	No	2.23%
36.68%	Technical	No	5.24%
9.51%	Not planning to work[b]	No	0.26%
18.4%	Other[c]	No	10.00%
4.49%	Will be in school[d]	No	0.23%

Notes: [a] Percent of those not in the labor force because they are keeping house with a bachelor's degree or more. [b] Percent of those not in the labor force with a bachelor's degree or more. [c] Percent of population with a bachelor's degree or more. [d] Percent of those not in labor force because they are in school with a bachelor's degree or more. The total number of students in the 1992 survey with nonmissing responses to this question is 16,258.

Table 2: Labor-Market-Knowledge Types

Labor-market-knowledge type	Label	Job goal	Perceived educational requirements	Percent
1	Not on college track	Noncollege job	College degree not required	23.8%
2	Overestimator	Noncollege job	College degree required	22.0%
3	Underestimator	College job	College degree not required	5.5%
4	On college track	College job	College degree required	48.7%

Table 3: Means of Student and School Characteristics by Information-Capital Type

	Information-capital type				p-values of F-tests that coefficients are equal		
Variable	Not on college track	Over-estima-tors	Under-estima-tors	On college track	Types 1 and 2	Types 1 and 3	Types 2 and 3
GPA	2.621*** (0.014)	3.067*** (0.014)	2.792*** (0.025)	3.283††† (0.008)	0.000	0.000	0.000
8th grade std. test composite	46.441*** (0.199)	52.724*** (0.202)	49.031*** (0.357)	56.381††† (0.112)	0.000	0.000	0.000
Reading pro-ficiency	1.023*** (0.014)	1.304*** (0.014)	1.144*** (0.024)	1.469††† (0.008)	0.000	0.000	0.000
Math pro-ficiency	1.105*** (0.021)	1.666*** (0.022)	1.278*** (0.038)	1.927††† (0.012)	0.000	0.000	0.000
Science pro-ficiency	0.792*** (0.016)	1.077*** (0.016)	0.903*** (0.028)	1.223††† (0.009)	0.000	0.000	0.000
Take algebra	0.234*** (0.011)	0.436*** (0.011)	0.291*** (0.020)	0.532††† (0.006)	0.000	0.006	0.000
Held back a grade	0.204*** (0.007)	0.116*** (0.007)	0.117*** (0.012)	0.069††† (0.004)	0.000	0.000	0.908
Locus of control	-0.123*** (0.012)	0.085*** (0.013)	-0.073*** (0.022)	0.171††† (0.007)	0.000	0.035	0.000
Self-concept	-0.094*** (0.014)	0.083 (0.014)	-0.108*** (0.024)	0.102††† (0.008)	0.000	0.600	0.000
SES	-0.384*** (0.015)	0.096*** (0.016)	-0.339*** (0.028)	0.260††† (0.009)	0.000	0.127	0.000
Age	14.442*** (0.012)	14.316*** (0.012)	14.317*** (0.021)	14.239††† (0.007)	0.000	0.000	0.988
Female	0.432*** (0.010)	0.419*** (0.011)	0.645*** (0.019)	0.582††† (0.006)	0.324	0.000	0.000

Asian/Pacific Islander	0.029*** (0.005)	0.066*** (0.005)	0.037*** (0.009)	0.084††† (0.003)	0.000	0.417	0.004
Hispanic	0.132*** (0.007)	0.111** (0.007)	0.130*** (0.012)	0.097††† (0.004)	0.008	0.908	0.122
Black	0.091* (0.006)	0.098*** (0.006)	0.096 (0.011)	0.079††† (0.003)	0.289	0.644	0.841
Native American	0.012*** (0.002)	0.009 (0.002)	0.014** (0.004)	0.006††† (0.001)	0.317	0.470	0.180
White	0.737 (0.009)	0.716* (0.010)	0.723 (0.017)	0.734††† (0.005)	0.059	0.418	0.712
Non-English dominant	0.110 (0.007)	0.110 (0.007)	0.119 (0.012)	0.108††† (0.004)	0.983	0.504	0.514
Single-parent household	0.172*** (0.008)	0.155** (0.008)	0.183*** (0.014)	0.140††† (0.004)	0.065	0.445	0.057
Discuss studies with parents	0.438*** (0.011)	0.566*** (0.011)	0.517*** (0.019)	0.620††† (0.006)	0.000	0.000	0.013
Smoke	0.067*** (0.004)	0.035 (0.004)	0.056*** (0.008)	0.030††† (0.002)	0.000	0.161	0.009
12th grade std. test composite	45.291*** (0.193)	52.177*** (0.197)	48.158*** (0.346)	56.357††† (0.110)	0.000	0.000	0.000
Guidance faculty per 10th grader	0.021 (0.001)	0.021 (0.001)	0.019*** (0.001)	0.022††† (0.000)	0.830	0.063	0.085
Vocational faculty per 10th grader	0.032*** (0.001)	0.024** (0.001)	0.028*** (0.001)	0.022††† (0.000)	0.000	0.000	0.001
Number of AP courses	4.309*** (0.134)	5.644** (0.136)	4.283*** (0.238)	5.995††† (0.075)	0.000	0.917	0.000
Percent attending 2-year	21.823*** (0.331)	19.637** (0.336)	21.197*** (0.591)	18.996††† (0.186)	0.000	0.316	0.013
Percent attending 4-year	38.067*** (0.574)	49.460*** (0.581)	39.262*** (1.021)	53.148††† (0.322)	0.000	0.269	0.000
10th grade enrollment	302.758 (5.052)	317.629 (5.128)	319.615 (9.014)	310.941††† (2.840)	0.013	0.077	0.836
Student-teacher ratio	16.212*** (0.103)	15.853* (0.105)	16.492*** (0.185)	15.672††† (0.058)	0.003	0.153	0.001

Percent non-White	26.055 (0.625)	26.286** (0.635)	26.526 (1.113)	25.029††† (0.352)	0.755	0.689	0.839
Percent free lunch	22.823*** (0.438)	17.266*** (0.445)	21.396*** (0.781)	15.617††† (0.246)	0.000	0.084	0.000
Urban	0.214*** (0.009)	0.303** (0.009)	0.232*** (0.017)	0.326††† (0.005)	0.000	0.307	0.000
Suburban	0.376*** (0.010)	0.415 (0.010)	0.421 (0.018)	0.405††† (0.006)	0.001	0.017	0.753
Rural	0.410*** (0.009)	0.282 (0.010)	0.347*** (0.017)	0.269††† (0.005)	0.000	0.000	0.000
Northeast	0.159*** (0.008)	0.207 (0.008)	0.186* (0.015)	0.214††† (0.005)	0.000	0.076	0.185
North Central	0.296*** (0.009)	0.256 (0.009)	0.284 (0.016)	0.259††† (0.005)	0.000	0.502	0.107
South	0.349 (0.010)	0.330 (0.010)	0.324 (0.017)	0.335††† (0.005)	0.082	0.165	0.766
West	0.196 (0.008)	0.207* (0.008)	0.206 (0.015)	0.192††† (0.005)	0.240	0.536	0.908

Notes: This table contains results from separate regressions of each student- and school-level variable on dummies for labor-market alignment type. Type 4 is the omitted category; the regression constant gives its mean. I add the coefficients on each of Types 1-3 to the regression constant to obtain the means for Types 1-3. * indicates that the mean for Type 1, 2, or 3 is significantly different from the Type 4 mean at the 10% level, ** at the 5% level, and *** at the 1% level. ††† indicates that the Type 4 mean is significantly different from zero at the 1% level.

Table 4: Information Capital Predicts Holding a College Job

	Specification				
Information-capital type	(1)	(2)	(3)	(4)	(5)
1	-0.252***	-0.176***	-0.163***	-0.158***	-0.155***
(Noncollege track)	(0.013)	(0.019)	(0.019)	(0.019)	(0.021)
2	-0.112***	-0.093***	-0.090***	-0.082***	-0.089***
(Overestimator)	(0.016)	(0.019)	(0.019)	(0.019)	(0.022)
3	-0.214***	-0.155***	-0.132***	-0.135***	-0.161***
(Underestimator)	(0.024)	(0.031)	(0.032)	(0.032)	(0.034)
Covariates included					
8th grade ability, achievement, coursetaking, and noncognitive measures	No	Yes	Yes	Yes	Yes
Age, gender, race and ethnicity, SES	No	No	Yes	Yes	Yes
Household environment and preferences	No	No	No	Yes	Yes
12th grade standardized test composite	No	No	No	No	Yes
High school FE	Yes	Yes	Yes	Yes	Yes
Regression statistics					
Number of obs.	8776	6283	6187	6076	5082
Adjusted R-squared	0.191	0.226	0.231	0.230	0.222

Notes: The dependent variable is "college job in 2000." Linear probability results reported; probit results show the same signs and significance levels. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Robust standard errors and appropriate panel weights are used. Type 4 (students on the college track) is the omitted category.

**Table 5: Effect of Labor-Market Knowledge on Wages,
Comparing Overestimators to Noncollege-Track Students on Noncollege Jobs**

	Specification				
Coefficient	(1)	(2)	(3)	(4)	(5)
T_2 (Overestimators)	0.048* (0.027)	-0.038 (0.037)	-0.031 (0.036)	-0.028 (0.037)	-0.027 (0.042)
Covariates included					
8th grade ability, achievement, coursetaking, and noncognitive measures	No	Yes	Yes	Yes	Yes
Age, gender, race and ethnicity, SES	No	No	Yes	Yes	Yes
Household environment and preferences	No	No	No	Yes	Yes
12th grade standardized test composite	No	No	No	No	Yes
High school FE	Yes	Yes	Yes	Yes	Yes
Regression statistics					
Number of obs.	2974	1994	1973	1928	1621
Adjusted R-squared	0.182	0.213	0.266	0.272	0.264

Notes: The dependent variable is log hourly wage in 2000, when the average age of respondents is 26. I restrict the sample to students who aspired to a noncollege job in 12th grade and who were employed in a noncollege job in 2000. OLS results reported. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Robust standard errors and appropriate panel weights are used. Type 1 (students not on the college track) is the omitted category.

Table 6: Effect of Labor-Market Knowledge on Wages, Comparing Underestimators to Noncollege-Track Students

	Specification				
Coefficient	(1)	(2)	(3)	(4)	(5)
T_3 (Underestimators)	-0.091**	-0.150***	-0.066	-0.061	-0.081
	(0.045)	(0.057)	(0.055)	(0.054)	(0.055)
Covariates included					
8th grade ability, achievement, coursetaking, and noncognitive measures	No	Yes	Yes	Yes	Yes
Age, gender, race and ethnicity, SES	No	No	Yes	Yes	Yes
Household environment and preferences	No	No	No	Yes	Yes
12th grade standardized test composite	No	No	No	No	Yes
High school FE	Yes	Yes	Yes	Yes	Yes
Regression statistics					
Number of obs.	2335	1565	1549	1514	1266
Adjusted R-squared	0.228	0.326	0.401	0.406	0.391

Notes: The dependent variable is log hourly wage in 2000, when the average age of respondents is 26. I restrict the sample to students who aspired to a noncollege job in 12th grade. OLS results reported. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Robust standard errors and appropriate panel weights are used. Type 1 (students not on the college track) is the omitted category.

**Table 7: Labor-Market Information and Job Tenure,
Comparing Overestimators to Noncollege-Track Students on Noncollege Jobs**

	Specification				
Coefficient	(1)	(2)	(3)	(4)	(5)
T_2 (Overestimators)	-0.429***	-0.609***	-0.583***	-0.530***	-0.376*
	(0.131)	(0.192)	(0.194)	(0.195)	(0.217)
Covariates included					
8^{th} grade ability, achievement, coursetaking, and noncognitive measures	No	Yes	Yes	Yes	Yes
Age, gender, race and ethnicity, SES	No	No	Yes	Yes	Yes
Household environment and preferences	No	No	No	Yes	Yes
12^{th} grade standardized test composite	No	No	No	No	Yes
High school FE	Yes	Yes	Yes	Yes	Yes
Regression statistics					
Number of obs.	3208	2152	2125	2076	1741
Adjusted R-squared	0.167	0.146	0.159	0.157	0.168

Notes: Job tenure is measured in years. OLS results reported. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Robust standard errors and appropriate panel weights are used. Type 1 (students not on the college track) is the omitted category.

Table 8: Labor-Market Knowledge and Educational Attainment, Comparing Overestimators to Noncollege-Track Students on Noncollege Jobs

	Specification				
Coefficient	(1)	(2)	(3)	(4)	(5)
T_2 (Overestimators)	0.968***	0.630***	0.534***	0.537***	0.514***
	(0.074)	(0.102)	(0.100)	(0.103)	(0.111)
	Covariates included				
8^{th} grade ability, achievement, coursetaking, and noncognitive measures	No	Yes	Yes	Yes	Yes
Age, gender, race and ethnicity, SES	No	No	Yes	Yes	Yes
Household environment and preferences	No	No	No	Yes	Yes
12^{th} grade standardized test composite	No	No	No	No	Yes
High school FE	Yes	Yes	Yes	Yes	Yes
	Regression statistics				
Number of obs.	3180	2132	2104	2056	1722
Adjusted R-squared	0.295	0.354	0.391	0.396	0.409

Notes: Educational attainment is a categorical variable taking values from one through seven (1 = less than high school, 2 = high school graduate, 3 = some postsecondary but no degree or certificate, 4 = certificate, 5 = associate's degree, 6 = bachelor's degree, 7 = graduate degree). OLS results reported; ordered probit results show the same signs and significance levels. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Robust standard errors and appropriate panel weights are used. Type 1 (students not on the college track) is the omitted category.

Table 9: Labor-Market Information and Job Tenure, Comparing Underestimators to Noncollege-Track Students

Coefficient	Specification (1)	(2)	(3)	(4)	(5)
T_3 (Underestimators)	-0.359*	-0.337	-0.153	-0.120	0.104
	(0.190)	(0.283)	(0.282)	(0.286)	(0.313)
Covariates included					
8th grade ability, achievement, coursetaking, and noncognitive measures	No	Yes	Yes	Yes	Yes
Age, gender, race and ethnicity, SES	No	No	Yes	Yes	Yes
Household environment and preferences	No	No	No	Yes	Yes
12th grade standardized test composite	No	No	No	No	Yes
High school FE	Yes	Yes	Yes	Yes	Yes
Regression statistics					
Number of obs.	2510	1679	1661	1624	1359
Adjusted R-squared	0.135	0.137	0.144	0.133	0.156

Notes: Job tenure is measured in years. OLS results reported. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Robust standard errors and appropriate panel weights are used. Type 1 (students not on the college track) is the omitted category. Unreported F-tests of the joint significance of all covariates yield p-values greater than 0.1 in specifications (2) through (5).

Table 10: Labor-Market Knowledge and Educational Attainment, Comparing Underestimators to Noncollege-Track Students

	Specification				
Coefficient	(1)	(2)	(3)	(4)	(5)
T_3 (Underestimators)	0.462*** (0.105)	0.341** (0.142)	0.362*** (0.139)	0.349** (0.139)	0.316** (0.149)
	Covariates included				
8th grade ability, achievement, coursetaking, and noncognitive measures	No	Yes	Yes	Yes	Yes
Age, gender, race and ethnicity, SES	No	No	Yes	Yes	Yes
Household environment and preferences	No	No	No	Yes	Yes
12th grade standardized test composite	No	No	No	No	Yes
High school FE	Yes	Yes	Yes	Yes	Yes
	Regression statistics				
Number of obs.	2497	1669	1650	1614	1347
Adjusted R-squared	0.245	0.306	0.342	0.348	0.369

Notes: Educational attainment is a categorical variable taking values from one through seven (1 = less than high school, 2 = high school graduate, 3 = some postsecondary but no degree or certificate, 4 = certificate, 5 = associate's degree, 6 = bachelor's degree, 7 = graduate degree). OLS results reported; ordered probit results show the same signs and significance levels. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Robust standard errors and appropriate panel weights are used. Type 1 (students not on the college track) is the omitted category.

Table 11: The Relationship Between School Inputs and Labor-Market Knowledge

Independent variables	Overestimators	Underestimators	College-track students
Guidance faculty per 10th grader	2.151 (4.019)	-5.451 (5.088)	-0.311 (3.117)
Vocational faculty per 10th grader	-5.575** (2.609)	-2.085 (4.068)	-6.380** (2.668)
	Regression statistics		
Number of observations		3831	
Pseudo R-squared		0.176	

Notes: Table 11 contains the results from a multinomial logit regression of information-capital type on student, school, and zip-code characteristics. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. Type 1 (noncollege-track students) is the base category. Standard errors are clustered at the school level.