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Student Uncertainty and Major Choice: A Robust Control Approach*

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Abstract

This paper examines how model uncertainty affects students' choice of major. The students, we assume, do not know the true wage distribution associated with each major. In response to this uncertainty, the students apply a max-min operator to their optimization problem, leading them to choose the major that performs best under the worst-case alternative wage distribution. This behavior is consistent with experimental evidence and the robust control literature. We show analytically that greater uncertainty about a particular major causes the student to be less likely to choose that major and that greater uncertainty across all majors causes fewer students to major in science, technology, engineering, and math (STEM) majors. To test the model's predictions, we have conducted a survey of college freshmen. The results from this survey are consistent with the theoretical model.

JEL Classification Codes: D81, I23, J24

Keywords: Major choice, model uncertainty, STEM.

*This paper involves the collection of data on human subjects, and we have obtained Institutional Review Board (IRB) approval from the College of the Holy Cross, Clark University, and Worcester Polytechnic Institute.

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1 Introduction

One of the most important decisions an undergraduate student must make is the selection of a major course of study. This decision impacts future career opportunities, potential earnings, and the likelihood of being employed. Students must take many things into consideration when making this choice: aptitude for course materials, interest in the field, career options, and expected compensation. Amongst others, Mincer (1974) and Becker (1993) have explored the factors that influence major choice. In their models, students are assumed to have full information about the career options and potential earnings of each possible major. The students then balance this information against the other relevant factors in choosing a major. These other factors have been explored more thoroughly in other studies using the same full information assumption.[1]

It has been long recognized, however, that college students do not possess the level of knowledge assumed in the above papers. In particular Betts (1996) and Arcidiacono et al. (2012) provide evidence that college students' expectations about future salaries and employment probabilities are often incorrect. This has led to new research that relaxes the assumption of full information. Specifically, Zafar (2011) and Wiswall and Zafar (2013) assume students face uncertainty about the true wage distribution associated with each major.[2] That is, the students believe that there are a number of alternative wage distributions that could be the actual distribution. Employing a Bayesian approach, the authors assume that the students place a prior distribution over all of the possible alternative wage distributions, which students then update as they obtain new information. The students can calculate an expected wage for each potential major based on the expected wage from each distribution weighted by the prior probability put on that distribution. Drawbacks of this approach are that it requires all students to specify a probability for each of the potentially infinite number of wage distributions and to update those priors using a relatively complex algorithm.

In this paper, we explore an alternative way that students may respond to model uncertainty. As we discuss below, this alternative approach is consistent with experimental evidence on how people behave in the face of model uncertainty. In our model of major choice, students do not know the true wage distribution for each major, similar to the assumption made in Zafar (2011) and Wiswall and Zafar

[1] Examples include Thompson et al. (2007), Seymour (1992), and Rask (2010) (which look at retention in STEM majors); Crip et al. (2009) Griffith (2010), and Price (2010) (which look at Hispanic and female enrollments in STEM fields); and Arcidiacono (2004) and Arcidiacono et al. (2011) (which look at ability sorting into majors and the affects of affirmative action).

[2] There are numerous papers in the education literature that have used the term "uncertainty" to characterize the case in which students know the true probability model generating the randomness and merely face uncertainty about the wage draw; examples include Tobias (2002), Nicholson (2002), Beffy et al. (2012), and Hartog et al. (2012). In the robust control and behavioral literatures, this type of "uncertainty" has typically been labeled as "risk" in order to distinguish it from the case in which agents do not know the true probability model. The latter case – called model uncertainty – is the focus of this paper.
At the end of section 3, we provide numerous salient differences between model uncertainty and risk aversion.

(2013). In stark contrast to those papers, the students do not place a prior over the set of alternative wage distributions.[3] This assumption follows the robust control literature and in particular Hansen and Sargent (2007).[4] Assuming that the students are uncertainty averse and have a preference for robustness, each student applies a max-min operator to their optimization problem. This operator induces each student to choose the major that maximizes her subjective expected utility, where the expectation is taken with respect to the worst-case wage distribution within the set of possible alternative distributions. In effect, this behavior ensures that the student's subjective expected utility never falls too far, regardless of which distributions happen to be true.

In this setting, we show that uncertainty has two major consequences for major choice. First, if a student faces greater uncertainty about one major's wage distribution relative to another, then all else equal, the student is weakly less likely to enroll in that major. Intuitively, this stems from the fact that greater uncertainty increases the size of the set of possible alternative wage distributions, which then leads the students to fear an even worse worst-case distribution. As a consequence, the students' subjective expected wage associated with that major falls, pushing the previously marginal students to choose a different major. This analytical result does not depend on specific assumptions about the set of wages associated with the majors.

Second, a change in the overall level of uncertainty influences the distribution of students across majors. To obtain this second result, we assume that the students' approximating wage distribution for each major happens to be the empirical wage distribution, as described in the American Community Survey. With this assumption, we can show numerically that an increase in uncertainty across all majors leads to a systematic re-sorting of students across majors. In particular, we offer evidence that greater uncertainty leads fewer students to major in science, technology, engineering, and mathematics (STEM) majors in favor of non-STEM majors. This second conclusion could potentially help explain the often-cited shortage of STEM majors, including The President's Council on Jobs and Competitiveness (2011), Paglin and Ruffalo (1990), and Arcidiacono (2004). This also suggests that new policy reforms aimed at providing students with additional information about the distribution of wages of past graduates may also impact the distribution of majors.[5]

We then test the model's prediction that a student's subjective expected wage increases as uncertainty falls (as measured by increased familiarity) by conducting a survey of over 350 college freshmen. Along

[3]In Bayesian analysis, it is assumed that students can place specific weights on how likely each distribution is to be true, while in our model students do not assign any weights to the distributions.

[4]The robust control approach has been used widely in the macroeconomics and finance literatures, including Barillas et al. (2009), Cagetti et al. (2002), Dennis (2007), and Ellison and Sargent (2012). Dennis et al. (2009), Levin and Williams (2003), and Walsh (2004) analyze how model uncertainty affects optimal monetary policy, while Karantounias et al. (2009) and Svec (2012) do the same for optimal fiscal policy. To our knowledge, this paper is the first one to apply robust control to an education model.

[5]An example of such a policy is the proposed bill "The Student Right to Know Before you Go" by Senator Ron Wyden of Oregon.

with demographic and other data, we elicit students' degree of familiarity with various major fields and their earnings expectations in those fields. If their responses are consistent with the theoretical model, we would expect to find that students who are more familiar with the wages associated with a major also have higher expected wages. Our survey results reflect this positive relationship. In addition, this finding provides support for our use of robust control over a Bayesian approach due to the fact that there is no a priori reason why a Bayesian model would predict that students' earnings expectations would systematically increase through the accumulation of additional information.

Since familiarity is the main driver in our model, we further explore the survey responses in order to examine the relationship between familiarity and observables. We find that men are more familiar with the physical and social sciences, while women are more familiar with health and biology. Given these findings, our theoretical model would predict that men would be more likely to have careers related to the physical and social sciences, while women would be more likely to have careers in health and biology. These predictions seem broadly consistent with patterns we see in employment data (Carnevale et al., 2011).

Our paper proceeds as follows. In section 2, we further discuss and justify our two key assumptions. In section 3, we introduce a simple theoretical model of major choice and derive both analytical and numerical results. Section 4 describes and analyzes a survey that provides evidence that familiarity is positively correlated with expected wages, as predicted by the model. In section 5, we discuss some additional implications of our work and conclude by offering policy suggestions.

2 Students and uncertainty aversion

Before we describe our model, it would be helpful to discuss our two key assumptions in more depth. The first key assumption is that students face uncertainty about the true wage distribution associated with each major. The second key assumption is that they respond to this uncertainty as if they are uncertainty averse. As we argue below, there is reason to believe that both of these assumptions are reasonable.

In regard to the first assumption, it is generally well-accepted that college students do not have perfect information about the career opportunities and employment prospects associated with each major. This lack of information may be attributable to the fact that college students, and freshmen in particular, have had little direct exposure to the employment characteristics of many different industries. Further, there are many factors that affect expected earnings, including macroeconomic trends, government policy (both domestic and foreign), technological progress, and changes in consumer preferences. As there is considerable uncertainty about the future paths of these factors, the expected wages associated with each major should also be uncertain to students.

The latter assumption – that students respond to uncertainty as if they are uncertainty averse – is consistent with much experimental evidence in the behavioral economics literature. Ellsberg (1961), for example, finds that many subjects dislike gambles with unknown odds and have a preference for gambles with known odds. He then suggests that one possible explanation of this finding is that the subjects believe that there is a set of probability models that could possibly characterize the gamble with unknown odds and that the subjects, when comparing the unknown-odds gamble to the known-odds gamble, pessimistically worry that the worst probability model is correct.

Since Ellsberg (1961), a number of laboratory experiments have confirmed the basic finding that many people behave as if they were uncertainty averse; see Camerer and Weber (1992) for an early review of the literature. Abdellaoui et al. (2011) and Halevy (2007), using Ellsberg-type experiments, show that people act as if they are uncertainty averse, though with a tremendous range of uncertainty aversion across people. Other research has suggested that uncertainty aversion might characterize the behavior of investors. Sarin and Weber (1993), for instance, show that German business students value assets with a known distribution of possible returns more highly than assets with uncertain returns. More recent evidence documenting investors' uncertainty aversion include Ahn et al. (2011) and Bossaerts et al. (2010). Finally, Anagol et al. (2011) provide evidence that children are uncertainty averse using a real-world test with Halloween costumes and candy.

3 Theoretical model

In this section, we formulate a simple, two-period model analyzing students' choice of a college major. In the initial period, $t = 0$, students must choose a major. Assume that there are k possible majors from which to choose: $\{m_1, m_2, ..., m_k\}$. Each major has two relevant characteristics. The first characteristic is the student's level of difficulty associated with completing each major and is modeled as a utility cost. Let d_i be the student's difficulty level of major m_i, where $i \in \{1, 2, ..., k\}$. Under this formulation, a student finds major 1 more difficult than major 2 if $d_1 > d_2$. We place no restriction on the distribution of difficulty levels across major. Given this, we can define a type of student as a unique combination of k difficulty parameters.[6]

The second characteristic of each major is the distribution of potential future wages associated with each major. Let $\{w_{ij}\}_{j=1}^{n_i}$ be the n_i possible future wages of a graduate who majored in m_i. One of the potential "wages" in this set is the sum of the transfers received if the graduate is unemployed after college. Let $\{\pi_{ij}\}_{j=1}^{n_i}$ be the probability distribution associated with each major's wages. Again, one of

[6] Although we discuss this parameter as the level of difficulty for a particular major, it can also be viewed as any factor unrelated to wages that affects the value a student derives from choosing a major. For example, d_i could be a measure of a student's level of enjoyment associated with major m_i or it could represent parental pressure, pushing a student to choose one major over another.

these probabilities represents the likelihood of being unemployed after graduating from major m_i.

The randomness in potential wages – the only randomness in the model – is resolved at $t = 1$, at which point the graduate receives a particular wage from within the set. As there are no further periods in the model, the graduate consumes her entire wage, which she values according to the concave utility function $u()$.

Given this setup, the objective of each student is to choose the major that maximizes the expected value of her lifetime utility. In making this choice, the student must compare each major's combination of difficulty and expected future wages. If we assume that students had rational expectations, then the expected utility of a student of type $\widehat{D} = \left\{\widehat{d_1}, \widehat{d_2}, ..., \widehat{d_k}\right\}$ choosing to major in m_i is

$$u_0 - \widehat{d_i} + \beta \sum_{j=1}^{n_i} \pi_{ij} u\left(w_{ij}\right)$$

where, by assumption, u_0 is a constant across all students and majors. With this formulation, we can determine the set of students that choose each major. As an example, all students whose type satisfies

$$d_1 \leq d_i + \beta \left[\sum_{j=1}^{n_1} \pi_{1j} u\left(w_{1j}\right) - \sum_{j=1}^{n_i} \pi_{ij} u\left(w_{ij}\right)\right], \forall i$$

choose major 1.

In this paper, though, our goal is to analyze how model uncertainty affects students' choice of majors. To this end, we assume that all students are endowed with an approximating model for each major. These k approximating models specify the probabilities associated with the potential future wages of each major. The students, however, are not confident that these approximating models correctly specify the true probability distributions for the majors. They worry that other probability models could potentially characterize the stochastic nature of each major's wages.[7] In order to ensure that these alternative models conform to some degree with the approximating model, we place restrictions on what types of alternative models are allowed. To do so, we follow the robust control literature, and in particular, Hansen and Sargent (2007).

For each major, we assume that each member of the set of alternative models is absolutely continuous with respect to that major's approximating probability model. This implies that the students only consider models that correctly put no weight on zero probability wage outcomes. The alternative models could place different weights on a major's wages than is specified by the approximating probability model, as long as the probability of that wage under the approximating probability model is between zero and one. Further, the assumption of absolute continuity implies that the Radon-Nikodym theorem holds,

[7] While we focus on earnings uncertainty, we acknowledge that there are other factors that students could be uncertain about, including the difficulty of each major. One benefit of focusing on earnings uncertainty is that we can obtain data on the empirical distribution of earnings for students in different majors.

which indicates that there exist measurable functions ϕ_i such that the expectation of a random variable X_i under the alternative models can be rewritten in terms of the approximating probability model:

$$\tilde{E}[X_i] = E[\phi_i X_i]$$

where $\tilde{E}$ is the subjective expectations operator. To guarantee that each alternative model is a legitimate probability model, we assume $E[\phi_i] = 1, \forall i$.

Using the functions ϕ_i, we can now define the distance between the alternative and approximating probability models to be the entropy:

$$\epsilon(\phi_i) \equiv E[\phi_i \log \phi_i],$$

a measure that is convex and grounded. Following the robust control literature, we will use this distance measure to define the students' multiplier preferences. The multiplier preferences characterize how the students value each of the possible majors.

The objective of each student is to choose the major, m_i, that maximizes the following criteria:

$$\min_{\phi_{ij}} \left\{ u_0 - d_i + \beta \sum_{j=1}^{n_i} \pi_{ij} \left[\phi_{ij} u(w_{ij}) + \theta_i \phi_{ij} \log \phi_{ij} \right] - \beta \theta_i \Psi \left[\sum_{j=1}^{n_i} \pi_{ij} \phi_{ij} - 1 \right] \right\}$$

where $\sum_{j=1}^{n_i} \pi_{ij} \phi_{ij} = 1$ is the legitimacy constraint.

The coefficients $\theta_i > 0$ are penalty parameters that index the degree to which the students are uncertain about the probability models for each major. A small θ_i indicates that the students are not penalized too harshly for tilting their probability model away from major i's approximating model. The *min* operator then yields a set of ϕ_{ij} that diverge greatly from unity. The resulting probabilities $\{\pi_{ij}\phi_{ij}\}$ are distant from the approximating model. Thus, a small θ_i captures student behavior when they face a large degree of uncertainty. A large θ_i means that the students face a sizable penalty for tilting their probability model away from the approximating model. As a result, the *min* operator yields a set of ϕ_{ij} close to unity, implying that the worst-case alternative model is close to the approximating model. Thus, a large θ_i captures student behavior when they face a small degree of uncertainty. As $\theta_i \to \infty$, this model collapses to the rational expectations framework discussed above. In this formulation, we allow students to face different levels of uncertainty in each major. This is meant to capture some of the variation in the students' backgrounds and interests.

Solving for the student's optimal choice of major is a two-step process. In the inner minimization step, the student fears that, for a given major choice, the worst-case probability model over the wages will occur. The solution that results from this minimization is the student's subjective expectation. The outer maximization stage determines the major that maximizes the student's expected utility, taking into account knowledge of the endogenous tilting of their expectation. The solution from this stage is the student's robustly optimal major. We will solve each of the steps in turn, starting with the inner minimization problem.

3.1 Inner minimization step

The first order condition with respect to ϕ_{ij} is

$$u(w_{ij}) + \theta_i(1 + \log\phi_{ij}) - \theta_i\Psi = 0$$

Combining this condition with the legitimacy constraint, we can determine the optimal values of ϕ_{ij}. Following this procedure, we get

$$\phi_{ij} = \frac{\exp\left(-\frac{u(w_{ij})}{\theta_i}\right)}{\sum_{j=1}^{n_i}\pi_{ij}\exp\left(-\frac{u(w_{ij})}{\theta_i}\right)} \tag{1}$$

This equation describes the optimal subjective weights for major m_i. There are two factors that affect ϕ_{ij}. First, these probability weights depend upon θ_i. A large θ_i implies that the degree to which ϕ_{ij} diverge from unity is small. Consequently, the subjective probability model is close to the approximating model, and the student is not very pessimistic about her future wages. A lower θ_i implies that the probability tiltings are large. This means that the subjective probability model is more pessimistic, placing greater weight on low wage outcomes and smaller weight on high wage outcomes. Intuitively, this means that the student views the possible utility outcomes associated with major m_i as relatively worse.

The second factor that affects the distortions is the profile of utilities across states. Ceteris paribus, as the distance in the student's utility across states grows, then the degree to which the student tilts the subjective expectation away from the approximating probability model grows. That is, if one state offers much greater welfare for the student than does another state, the student will fear an alternative model that places a much higher weight on the low wage state and a much lower weight on the high wage state.

3.2 Outer maximization step

In the maximization step, the student chooses the major that performs well even if the worst-case probability model characterizes the randomness associated with each major. To determine this, we incorporate the optimal probability tiltings into the student's objective function. Doing this, we get

$$u_0 - d_i - \beta\theta_i\log\sum_{j=1}^{n_i}\pi_{ij}\exp\left(-\frac{u(w_{ij})}{\theta_i}\right) \tag{2}$$

Given this, the student now compares her expected lifetime utility across all majors in order to choose her optimal major. Using this equation, we can determine which types of students choose each major. As an example, a student chooses major m_1 if

$$d_1 \leq d_i + \beta \left[\theta_i \log \sum_{j=1}^{n_i} \pi_{ij} \exp\left(-\frac{u(w_{ij})}{\theta_i} \right) - \theta_1 \log \sum_{j=1}^{n_1} \pi_{1j} \exp\left(-\frac{u(w_{1j})}{\theta_1} \right) \right], \forall i \tag{3}$$

Using this equation, we derive the following theorem:

Theorem 1 *If a student's uncertainty about a particular major rises, then all else equal, the student is weakly less likely to enroll in that major.*

Proof. Without loss of generality, consider a rise in uncertainty for major 1. Letting

$$\bar{d}_1 \equiv d_i + \beta \left[\theta_i \log \sum_{j=1}^{n_i} \pi_{ij} \exp\left(-\frac{u(w_{ij})}{\theta_i} \right) - \theta_1 \log \sum_{j=1}^{n_1} \pi_{1j} \exp\left(-\frac{u(w_{1j})}{\theta_1} \right) \right]$$

for some alternative major m_i, (3) then says that a student will choose m_1 over that major m_i if d_1 is less than the threshold $\bar{d}_1$. So, to prove this theorem, we will show that $\frac{\partial \bar{d}_1}{\partial \theta_1} \geq 0$, where the inequality is strict whenever the distribution of wages is non-degenerate. The derivative of $\bar{d}_1$ with respect to θ_1 is

$$\frac{\partial \bar{d}_1}{\partial \theta_1} = -\log \sum_{j=1}^{n_1} \pi_{1j} \exp\left(-\frac{u(w_{1j})}{\theta_1} \right) - \left[\frac{\sum_{j=1}^{n_1} \pi_{1j} \exp\left(-\frac{u(w_{1j})}{\theta_1} \right) \frac{u(w_{1j})}{\theta_1}}{\sum_{j=1}^{n_1} \pi_{1j} \exp\left(-\frac{u(w_{1j})}{\theta_1} \right)} \right]$$

We want to show that $\frac{\partial \bar{d}_1}{\partial \theta_1} \geq 0$, meaning that

$$\sum_{j=1}^{n_1} \pi_{1j} \exp\left(-\frac{u(w_{1j})}{\theta_1} \right) \left(\frac{-u(w_{1j})}{\theta_1} \right) \geq \left[\sum_{j=1}^{n_1} \pi_{1j} \exp\left(-\frac{u(w_{1j})}{\theta_1} \right) \right] \log \left[\sum_{j=1}^{n_1} \pi_{1j} \exp\left(-\frac{u(w_{1j})}{\theta_1} \right) \right]$$

Letting $x_{1j} \equiv \exp\left(-\frac{u(w_{1j})}{\theta_1} \right) > 0$ and rearranging, we can show that this equation simplifies to

$$\sum_{j=1}^{n_1} \pi_{1j} x_{1j} \log(x_{1j}) \geq \left[\sum_{j=1}^{n_1} \pi_{1j} x_{1j} \right] \log \left(\sum_{j=1}^{n_1} \pi_{1j} x_{1j} \right) \tag{4}$$

Because $x \log(x)$ is strictly convex, then (4) holds with strict inequality whenever the distribution of x's is non-degenerate and (4) holds with equality whenever $x_{1j} = \bar{x}, \forall j$. Thus, $\frac{\partial \bar{d}_1}{\partial \theta_1} \geq 0$, and $\frac{\partial \bar{d}_1}{\partial \theta_1} > 0$ if $\{x_{1j}\}_{j=1}^{n_1}$ is non-degenerate. This same logic applies when comparing m_1 to any other major besides m_i. Thus, if m_1 was the student's preferred major, then a rise in uncertainty makes it less likely that the student will still prefer major 1; if m_1 was not the student's preferred major, then a rise in uncertainty has no effect.

Consequently, a rise in uncertainty makes a student weakly less likely to choose to enroll in that major. ■

Corollary 1 *As a student's uncertainty about a particular major rises, then all else equal, the student's subjective expected wage associated with the major falls.*

Proof. Equation (1) determines the optimal probability tilting. All else equal, as θ_i falls, the endogenous probability distortions diverge from unity, placing more subjective weight on the low wage outcomes and less subjective weight on the high wage outcomes. Consequently, the subjective expected wage of m_i falls with the level of uncertainty. ■

We have now shown that the level of uncertainty affects a student's choice of major. Specifically, a rise in a student's uncertainty about a particular major's future wages leads that student to be weakly less likely to enroll in that major. This occurs because the student's subjective expected wage – and hence, the student's subjective expected utility – from choosing that major decreases with the degree of uncertainty.

We would also like to explore how changes in the level of uncertainty across all majors affects major choice. As students cannot lower their probability of choosing all majors, greater uncertainty across all majors might have a distributional effect, altering how many students choose one set of majors over another. To study this, we must turn to the quantitative implications of the model, as the student's choice of major depends upon the actual distribution of wages associated with each major.

3.3 Quantitative results

In this section, we will quantitatively explore the predictions of the simple model presented above using wage and employment data collected from recent college graduates. Our goal in doing this is to examine whether the equilibrium distribution of majors depends on the level of uncertainty across all majors.

To do so, we make three modifications to the theory presented above. First, we assume that the students' level of uncertainty is the same in all majors: $\theta_1 = \theta_2 = ... = \theta_k \equiv \theta$. This assumption, while too restrictive, allows us to analyze a set of new policy initiatives currently being implemented around the United States that are aimed at providing students with more information about their potential future earnings by major. To give a brief example, public colleges and universities in the state of Virginia now post information online about the salaries and employment histories of past graduates by major. Thus, by making this assumption, we can predict the impact of the shift from one regime to another by varying the level of θ. In one possible regime, students face little uncertainty, as wage and employment information by major is available and known to the students when making their decisions. This regime, characterized by a high θ, reflects the policy initiatives mentioned above. In another possible regime, students face a large degree of uncertainty. In this regime, perhaps, colleges and universities do not provide wage and employment information to students and instead advisors are cautioned against discussing this information. This regime is characterized by a low θ. Thus, while we believe that students do in fact have different levels of uncertainty in different majors, this assumption allows us to capture the impact of a policy shift of this type.

Our second modification to the theory is that we assume that there are eleven possible major fields open to students: biology and life sciences, business, education, engineering, health, humanities and arts, law and public policy, mathematics and computer science, physical sciences, psychology and social work, and social science.[8] For each of these majors, let $d_i \in \{0.4, 0.5, ..., 1\}$, $\forall i$. This implies that there are 7 possible difficulty levels for each major. If there exists one student for each unique combination of difficulty levels, then there are 7^{11} total students. This assumption does not qualitatively change our conclusions.

For our third modification, we assume that all students within a particular major face the same set of potential wages and the same probability distribution over those wages. While we believe that in reality different students draw from different wage distributions based on their aptitude and skills, we abstract away from this variation and assume that all idiosyncratic differences across students are captured by differences in the difficulty parameters.

In addition to these theoretical modifications, we obtain actual wage and employment data for recent college graduates from The American Community Survey (ACS) Public Use Microdata Sample in 2011. In particular, we obtain the median, 25th percentile, and 75th percentile wages for each major listed above. With these data, we assume that students in each major face 4 possible wages at $t = 1$: the median wage in that major, the 25th percentile wage, the 75th percentile wage, and the transfers associated with being unemployed.[9] We assume that the students, if employed, have a 50% chance of earning the median wage and a 25% chance of earning either of the other two wages. We also pull data on the graduates' likelihood of unemployment after graduating from one of these eleven types of majors from ACS. These data allows us to form the wage and probability distribution for each of the eleven majors. These data are presented in Tables 1 and 2.

With these data and for a given value of θ, we can use (2) to determine the expected utility of each student for each major. This allows us to determine how many students choose each major for that given level of uncertainty. We then vary θ in order to see how the distribution of students across majors changes with the total level of uncertainty. In Table 3 below, we present the results.

Table 3 shows that the distribution of majors does indeed depend upon the level of θ. Evidently, in

[8] There are similar categories used in Carnevale et al. (2011). These categories are also used in our survey that follows.

[9] This value, following Shimer (2005), is 40% of the median wage or $14,000.

the regime with no uncertainty, almost half of all students choose to major in engineering and another third of students choose to major in either mathematics and computer science or in the physical sciences. It is no coincidence that this is the case, as these majors have the highest average wages and because the difficulty parameter is distributed uniformly across students. On the other end of the spectrum, when students are faced with a large degree of uncertainty across all majors, many fewer students choose to major in engineering, mathematics and computer science, or the physical sciences. In fact, less than 30% of students choose to major in these majors. Instead, the students are more evenly distributed across all majors, with a slight emphasis on education and health. To be clear, if a different difficulty distribution was chosen, the same qualitative pattern would appear: uncertainty is a factor driving students out of STEM majors.

Put another way, Table 3 shows that uncertainty might be a factor in the on-going shortage of STEM majors. This shortage has been discussed in a number of places, including The President's Council on Jobs and Competitiveness (2011), Paglin and Ruffalo (1990), and Arcidiacono (2004). If we suppose that today's college students live in a world with high uncertainty, then fewer students choose to major in engineering, math, and physical science than would in a different world in which students were better informed about each major's employment prospects and wages. Thus, model uncertainty could explain the relative dearth of STEM majors, a possibility that to our knowledge has not been explored in the education literature.

At this point, it is helpful to understand why uncertainty affects different majors differently. That is, why would a smaller θ encourage people to major in non-STEM majors and discourage people from majoring in STEM majors? To see the answer to this, first consider the extreme case where $\theta \to \infty$. At this value, students fully understand the wage and unemployment differences across the majors. As higher wages imply higher expected utility, the students naturally prefer the higher wage majors, for a given level of difficulty. Since the STEM majors have the highest expected wages out of all the eleven listed majors, many students choose to major in STEM. Next, consider a moderate value of θ, one that implies that students face a limited degree of uncertainty about the majors. This uncertainty means that students believe that the high wage outcomes are relatively less likely and the low wage outcomes are relatively more likely than under the approximating model. This change reduces the expected wage of the STEM majors by more than that of the non-STEM majors because all majors share the same value for the low wage outcome while the STEM majors offer the largest high wage outcome. Consequently, the previously marginal students shift out of the STEM majors and enter a non-STEM major, where the specific choice of non-STEM major depends upon the particular wages and employment probabilities of the other majors and the difficulty parameters. Finally, consider the other extreme case in which $\theta \to 0$. This value implies that the students face an immense amount of uncertainty. In this extreme environment, students discount the possibility that they will be employed at all, regardless of their choice of major. As a result, the students make their major choice based entirely on their difficulty parameters. As such, we should see that the students are more evenly distributed across all the majors, a result seen in Table 3.

3.4 Model uncertainty and risk aversion

Briefly pausing from the main narrative, we would like to highlight that our discussion thus far has focused on the impact of model uncertainty on students' choice of college major. However, it is well-known that there is a degree of similarity between risk aversion and model uncertainty; see Barillas et al. (2009) and Hansen and Sargent (2007). Specifically, increasing a student's risk aversion would have some of the same impacts on the choice of major as increasing the student's model uncertainty.

That being said, there are a number of salient differences between model uncertainty and risk aversion. First, and most important, the motivations underlying the students' choices are different in the two cases. In this model uncertainty story, a student chooses a particular major because her uncertainty about the true, major-specific wage distributions leads her to fear potentially harmful alternative wage distributions. In a risk aversion setup, though, a student chooses a particular major, knowing the true wage distribution for each major, but disliking the wage risk. Second, a student's model uncertainty can vary by major, while a student's risk aversion is independent of the major. Third, a model centered around risk aversion cannot account for differences in the information held by students that are major specific.

Finally, the distinction between model uncertainty and risk aversion is important because the policy implications are vastly different. If students face model uncertainty, then their choices are distorted relative to a rational expectations framework. That is, if students are presented with better information, they would make different – and welfare-improving – choices. This distortion reveals the possibility that certain policies could help raise the students' welfare. If students are merely risk averse, though, their choices would be optimal given their preferences. This implies that no policy could raise the students' welfare.

4 Survey Description and Results

We have shown theoretically that greater uncertainty about a particular major's wage distribution discourages students from choosing that major. This occurs because, as uncertainty rises, the subjective expected wage associated with that major falls. Further, after combining the theoretical model with wage and employment data, we have found that greater uncertainty across all majors influences the distribution of students across majors. In fact, we have shown that greater uncertainty across all majors seems to dissuade students from majoring in STEM majors in favor of non-STEM majors.

One testable prediction made by the theoretical model is that as a student's uncertainty about a particular major rises, her expected wage falls. To test this prediction, we have conducted a survey of college freshmen. We describe that survey and its results below, including a look at the relationship between familiarity and gender.

4.1 Survey Description

Our survey was administered to first-semester freshmen at three undergraduate institutions in the Worcester, Massachusetts area: The College of the Holy Cross, Clark University, and Worcester Polytechnic Institute (WPI). Holy Cross is an undergraduate-only liberal arts college without an in-house engineering program.[10] Clark is a university with both undergraduate and graduate schools. WPI is primarily an engineering school, but also offers degrees in business and the arts and sciences. The entire freshman class at each institution was solicited via email. Email communications included a link to the survey and offered respondents a chance to win one of six \$50 gift certificates. Follow-up participation requests were sent periodically throughout the survey period. In total, 359 freshmen completed the survey. Of those respondents, 173 were from Holy Cross (23 percent response rate), 114 were from Clark (19 percent), and 72 were from WPI (8 percent).[11] The description of the results that follow will be based on a restricted subset of these respondents. Specifically, a small number of respondents gave infeasible responses to key questions and were thus eliminated from the calculations and analysis that follows.[12]

The survey has a number of questions, the most important of which asks the students to identify their level of familiarity and expected average salaries in eleven different sets of majors.[13] The sets of majors are listed in Table 4, and the full text of the survey can be found in Appendix Section A. We assess an individual's familiarity with each set of majors in multiple ways. First, respondents are asked if a family member or close acquaintance majored in or has a career related to each set of majors. Having a family member or close acquaintance in that field would presumably increase the student's level of familiarity with that field. Next, respondents are asked directly to rate their familiarity with the employment prospects and salaries of the major categories on a scale from one to seven. For these last two questions, respondents

[10] There is a program between Holy Cross and WPI that allows a Bachelor of Arts degree to be earned at Holy Cross and a Masters of Science in Engineering degree to be earned at WPI.

[11] Our sample is mostly representative of the population based on the observables, which are the respondents' gender, race, college residential status, and financial aid status. It is representative for Holy Cross, while there are slightly less residential students and students on financial aid in our sample at Clark. At WPI, there are slightly more females and slightly less students on financial aid in our sample.

[12] Specifically, a number of respondents gave very low or very high values in response to questions about the average salaries in major fields. We eliminated the responses of those that identified any major as having an average salary below \$1,000 or above \$1,000,000.

[13] The theoretical model explores the implications of uncertainty, and yet we asked questions about a student's familiarity in the survey. The reason for this difference is that we felt that the students would better understand the meaning of "how familiar are you" questions compared to "how uncertain are you" questions. It also seemed natural to us that familiarity represents the inverse of uncertainty. In this way, we believe that our survey results test the mechanism and predictions of our theoretical model.

are instructed that a rating of 1 represents “not familiar” and that a rating of 7 represents “extremely familiar.”

Table 5 presents the results from these familiarity questions for each set of majors for the full sample. In that table, we list the means and standard deviations of the students’ responses to these familiarity questions. Respondents were most likely to have a family member or close acquaintance who had majored in the fields of business, education, engineering, and health. They were least likely to have a family member or close acquaintance in the areas of the physical sciences, biology, psychology, and the social sciences. Consistent with what one would assume, students reported being most familiar with both employment prospects and wages in the same areas where they were most likely to report a close acquaintance or family member. This finding can be seen in Table 6, which reports the correlation matrix for all three familiarity variables. Given the particularly high correlation between the responses for the familiarity with employment prospects and the familiarity with wages, we concentrate on using the students’ familiarity of their future earnings in the analysis that follows. This focus does not qualitatively affect our results.

After students were asked about their familiarity with individual fields, they were then asked about their expectations regarding major-specific average salaries. To get at the dependence of this average salary on future schooling decisions, we decided to ask this question in two ways. First, we asked for the average salary of a typical student who had majored in a particular major, taking into account all of the possible career paths and educational possibilities available to the student. This question required the student to mentally calculate an expected salary across possible career paths, educational attainment levels, and tenure. Second, we asked for the average salary of a typical student who had majored in a particular major, but did not go on to graduate school. This question required the student to calculate an average across possible career paths and tenure levels. We have chosen to ask respondents about the expected wages of the “typical” student rather than their own expected wage for two primary reasons. First, the purpose of the survey was not to directly explain a particular student’s choice of major, but simply establish the link between familiarity and wage expectations. Second, we wanted to isolate the relationship between expected wages and familiarity, not an individual’s perception of their own aptitudes or opportunities which could affect their expected wages.

Table 7 presents the mean and standard deviations of the student responses to both questions. When asked about all graduates from each field of majors, including those who go on to receive advanced degrees, the fields of engineering, law, business, and health receive the highest average salaries while education, humanities, social sciences, and psychology have the lowest expected average salaries. The results are very similar if the survey respondents are asked to limit their estimates to those who have only received an undergraduate degree in the field and no advanced degrees. The predicted average earnings in this case fall by about 20 percent for most majors. That said, the relative salaries of those in the fields of law and health fall compared to other fields, perhaps reflecting a belief that advanced degrees are more necessary in these fields to fully capitalize on one's undergraduate education.

In addition to asking demographic questions, we asked the students to rate the difficulty of the courses (a rating of 1 represents "very easy" and a rating of 7 represents "almost impossible") in each field of majors and their likelihood of finding employment after graduation if they chose that major field. In Table 8, we present a summary of these responses. Evidently, engineering and other sciences are perceived to be more difficult and have higher employment prospects than other major fields of study.

4.2 Familiarity and Expected Wages

In this section, we explore the relationship between students' familiarity and their expected wages. The theoretical model above assumes that students are uncertainty averse. This assumption implies that greater familiarity (and so, less uncertainty) raises the students' subjective expected wages. This implication is testable using our survey results. If our theoretical model is to be trusted, we should expect to find that students report higher expected salaries in fields where they report more familiarity.

To examine the relationship between uncertainty and expected wages, we run two regressions.[14] In the first regression, we use ordinary least squares to regress the log of the expected average salaries by major on the students' familiarity levels. As mentioned above, we use the students' reported level of familiarity with earnings to proxy for uncertainty. In addition, we include demographic characteristics (gender, age, race), a proxy for family income (whether the respondent receives any federal financial aid), and dummies for each major as independent variables. In the second regression, we use fixed effects to control for any within-individual differences in expected wage levels or the scale used to rate familiarity. We again include the dummies for each major as a control variable.

The results of the first regression appear in column [1] of Table 9. The key finding is that a one unit increase in an individual's self-evaluated level of familiarity (and thus a reduction of uncertainty) is related to a 4.8 percent increase in the expected wage for any given major. The t-statistic of 11.52 indicates that this result is statistically significant at the 1% level.

One may be concerned that different groups of individuals use systematically different ranking scales when answering questions about familiarity. For example, the results in column [1] could be explained if those with lower salary expectations for all majors give consistently lower ranks for their level of familiarity with each major. To address this possibility, we have used a fixed effects model to produce the results in column [2]. Though we do find a small drop in the coefficient on the familiarity term, the 4.0 percent increase in the average wage reported for each unit increase in the familiarity rating is still significant at

[14] The results that follow are based on the survey respondents' estimates of the average income of all graduates from a major, not just those without advanced degrees. Using the respondents' other estimates of average wages for those who do not get an advanced degree are not qualitatively different and can be found in Appendix Table 1.

the 1% level. In both specifications, our survey results strongly support the predictions of our theoretical model.

We would also like to note that our empirical finding that expected wages are positively related to familiarity is consistent with uncertainty aversion and robust control but not particularly consistent with a Bayesian approach. This is because, in a Bayesian model, there would be no reason to believe that students wage expectations would be systematically related to their familiarity, let alone positively related. Intuitively, each students prior could either be lower or higher than the true wage distribution and so new information would either increase or decrease her wage expectations, respectively. As there is no reason to believe that students generally have priors that are lower than the true distribution, one would not expect to see a systematic relation between wages and familiarity. Consequently, because we do find a systematic and positive relationship between wages and familiarity, we believe that the data supports our choice of robust control over a Bayesian approach.

4.3 Familiarity and Observables

Given the finding that greater familiarity with a particular major is linked to higher expected wages in a major and the theoretical link between familiarity and major choice, we thought it would be interesting to examine the relationship between students' reported familiarity values and gender.[15] If we do find a relationship, it could help explain broad patterns of why we find certain jobs to be dominated by one gender. So, in the rest of this section, we analyze whether there is a connection between gender and familiarity.

Table 10 presents our initial test of this connection. Specifically, the first two columns of Table 10 reports the average value of the students' familiarity with earnings, broken down by gender. The third column then tests whether the two values are statistically different from each other. Males report a higher familiarity score in the physical and social sciences. In addition, mathematics and computer science and engineering were close to being significant at traditional levels. These results, though somewhat consistent with the idea that more men enter math and the sciences than women, suffer from the possibility that men, on average, report higher familiarity scores than women.

To mitigate this possibility, we report the number of standard deviations the familiarity score is from each individual's mean across all majors in the remaining columns of Table 10. To give an example of this, suppose the average familiarity value reported by an individual was 3.5 and that her standard deviation was 1. Then, if the reported familiarity level of this individual in law was 3, we give law a value of -0.5 because it is half a standard deviation below her mean. Following this procedure for all individuals

[15] Appendix Section B uses the survey data to examine the possible direct link between familiarity and major choice. Due to endogeneity concerns, the causal direction is difficult to ascertain and we therefore leave it to the interested reader to explore this relationship in the Appendix.

and all majors, we report the average deviations by gender in the columns 4 and 5 of Table 10. In the sixth column, we again test for the difference between these values. We find that men report having greater familiarity with the physical and social sciences, while women report having greater familiarity with biology, health, and psychology. Other than for psychology, all of these differences are significant at the 5 percent level or better. These results might help explain why men seem to gravitate towards the physical and social sciences and why women seem to gravitate towards health related fields (Carnevale et al. (2011) and American Association of Medical Colleges (2012)).

We have examined the same two types of tables focusing on race, but we have found little differences between the racial groups. One likely explanation for this is that the three Massachusetts colleges and universities tend to be predominately white. In fact, 81% of our survey respondents are white, while only 3% are black and 3% are Latino. In the future, we are interested in examining whether race is related to familiarity by surveying a wider variety of schools.

5 Discussion and Conclusion

In the sections above, we have shown that uncertainty can influence students' expectations of earnings and choice of majors. In our simple theoretical model, we find that greater uncertainty within a particular major pushes students away from that major and that greater uncertainty across all majors might push students into non-STEM majors. We have also provided direct evidence from a survey that students indeed respond to uncertainty in the manner predicted by our robust control model and not a Bayesian model.

An interesting point about the impact of this uncertainty involves the potential feedback loop between wages and the number of college majors in that field. Many presume that, if there is a shortage of graduates in a particular field, then the wages associated with that major will rise; this, in turn, would be expected to induce an influx of students into that major. However, this model suggests that the feedback loop might be relatively insensitive. That is, even if there is a shortage of graduates in a field and wages rise, many students might decide not to enter that major because of their uncertainty. At high levels of uncertainty, the students discount the high wages, fearing that they would not be likely to achieve those salaries. This then implies that, even though wages in the STEM majors are relatively high, a relatively small number of students would enter that major.

A simple policy change might mitigate the deleterious effects of uncertainty: colleges and universities should be more transparent about the future prospects of students in each major. This increased information would allow students to choose majors knowing the actual wage and employment data, rather than guarding against the future worst-case scenarios. In fact, this policy change is already being implemented by individual schools[16], many states[17], and is being considered at the national level.[18] These initiatives, by reducing student uncertainty, should help students make informed decisions about their college major, a decision that has a large influence on their future employment opportunities. Also, if the theoretical model is correct, these policies should induce more students to choose STEM majors.

[16] The University of Chicago and The University of Texas

[17] In Virginia, for example, The State Council of Higher Education for Virginia has begun to post online the median wage by major and by school of Virginia graduates who are employed in Virginia. The Council also posts the percentage of graduates who are employed in Virginia and a measure of the graduates' wage dispersion by major. This initiative towards greater transparency is being replicated to varying degrees in Arkansas, Tennessee, Texas, Colorado, and Nevada (Marcus, 2013).

[18] "The Student Right to Know Before You Go" bill being proposed in Congress

Appendices

A Survey

Survey Title: Survey Regarding Majors

Administration: Internet via Survey Monkey

Rules: Forced responses to all questions prior to demographics section.

Incentive: Completion of the survey enters the respondent into a drawing to win one of six $50 gift cards.

Text of Survey:

Page 1:

Thank your for taking the time to complete this survey. The purpose of this study is to ascertain aspects of major choice through the following survey. As a thank you for participating you will be entered into a random drawing to win one of six $50 Amazon gift cards. E-mail addresses will be used to contact drawing winners.

Please remember participation in this study is entirely voluntary, and you may terminate your participation at any time. Your responses will only be identified by code number. Any mapping of names to e-mail addresses will be stored offline and destroyed after the completion of the project. Any questions about this survey and project may be direct to Dr. Anil Nathan (508-793-2680, anathan@holycross.edu).

Page 2:

1. For each of the categories below, please indicate whether you have a close family member or acquaintance that majored in or works in that field?

Response: Yes or No for each field listed in Table 4

Page 3:

2. For each of the categories below, please indicate your level of familiarity with that field's employment prospects?

Response: 1 - not familiar 2 3 4 5 6 7 - extremely familiar

Page 4:

3. For each of the categories below, please indicate your level of familiarity with that field's potential salaries?

Response: 1 - not familiar 2 3 4 5 6 7 - extremely familiar

Page 5:

4. For each of the categories below, how difficult do you believe the classes in that undergraduate field to be?

Response: 1 - very easy 2 3 4 5 6 7 - almost impossible

Page 6:

5. For each of the categories listed below, imagine that you have graduated from college with this as your major. How likely are you to find employment?

Response: 1 - very unlikely 2 3 4 5 6 7 - very likely

Page 7:

6. For each of the categories below, what is the average salary for a typical person with an undergraduate degree in that field? In coming up with your answer, please consider all of the possible career paths that one could take after graduation, including those that require a graduate degree.

Response: Free numeric response

7. For each of the categories below, what is the average salary for a typical person with ONLY an undergraduate degree in that field? In coming up with your answer, please consider all of the possible career paths that one could take after graduation?

Response: Free numeric response

Page 8:

8. Have you declared a major?

Response: Yes or No

9. In which of the following fields is your major? If you have not yet declared a major, in which field would you choose a major if you were forced to make a choice today?
Response: One of the fields listed in Table 4

Page 8:

10. What is your gender?
Response: Male, Female, or Prefer not to answer

11. What is your age?
Response: Free numeric response

12. Which of the following best fits how you would describe yourself?
Response: White, Black, Latino, Asian, or Other

Page 9:

13. Do you currently receive any form of federal financial aid (such as a Pell Grant, Subsidized Stafford Loan, or a Perkins Loan)?
Response: Yes or No

14. Are you a U.S. resident? Response: Yes or No

Page 10:

15. Thank you for completing the survey! Please provide the email address that we should use to contact you should you win our prize drawing.

B Familiarity and Major Choice

In Section 4, we examined whether the model's mechanism – namely, that familiarity is positively related to expected salaries – was relevant in an educational setting. We found strong evidence in support of that mechanism. In this section, we explore whether greater uncertainty (less familiarity) is correlated with a lower likelihood that a student will enroll in that major, as predicted by the theoretical model.

Appendix Table 2 presents the students' reported levels of earnings familiarity for their own major (or announced intended major) and compares that level with the familiarity score of all other majors. On average, respondents gave their intended major a familiarity rating of 4.6 out of 7 and all other majors a 3.4 rating. Thinking about the ratings in terms of rank order of familiarity based on these ratings, the respondents gave their intended major between the second and third highest ranking (average of 2.7) of the eleven major fields. Appendix Table 2 also presents this data by each major field that a respondent may have chosen. Though some fields have very few intended majors, most have at least 20 intended majors. With every major field, students' familiarity with their intended major averaged in the top half of their ratings and six fields had average rankings between one and two.

The average reported value of a major's perceived difficulty and employment prospects of each field of majors are also presented in Appendix Table 2. Though respondents tend to rate their intended major as more difficult and to have better employment prospects than more than half of the other majors, the values are much closer to the middle than their familiarity rankings. This suggests that there may be a clearer relationship between familiarity and major choice than other dimensions that contribute to the choice of major.[19]

Next we attempt to test the relationship between familiarity and intended choice of major. The coefficients in Appendix Table 3 are the mean marginal effects (MMEs) from a probit analysis predicting the probability that a particular major is chosen as a respondent's intended major.[20] The explanatory variable of interest is earnings familiarity, but we also include the respondents' major-specific reports of difficulty levels and the likelihood of employment following graduation as independent variables. Dummy variables for each major field are included in the probit analysis to account for any general trends in major choice.

Column [1] of Appendix Table 3 presents the MMEs if the values for earnings familiarity, difficulty of courses, and job prospects following graduation are used. The results show that a one unit increase in a respondent's familiarity rating increases the likelihood that they will choose a major by 2.5 percentage points. This finding is significant at the one percent level. The results suggest that familiarity is a more important predictor of major choice than the difficulty of the course work (0.6 percentage points per unit change and not significant at traditional levels) and on par with a one unit change in the rating for job prospects following graduation (2.3 percentage points per unit).

Rather than simply use the reported values of familiarity which do not provide any information on a

[19] We will address the possibility of an endogenous relationship between our familiarity measure and the choice of major below.

[20] Mean marginal effects present the average change in probabilities of a one unit change in a covariate based on the probit coefficients. The average is taken across all observations with all other variables valued at their reported value, not their mean value as would be used if calculating "marginal effects at the mean."

student's view of where one major field stands relative to others, a better approach would be to rank the fields of study based on these ratings. Specifically, we include the relative rankings of familiarity, difficulty, and employment prospects as explanatory variables and re-run the probit regression. The results from this specification can be found in Column [2] of Appendix Table 3. The MMEs for all categories have changed signs as the impact examined has changed from an increase in the familiarity, difficulty, or employment prospects to the drop of the ranking of those values by one unit. We see that a one unit drop in the rank of the familiarity with potential earnings (say from 1st to 2nd or 4th to 5th highest familiarity) is associated with a 1.8 percentage point decline in the probability of majoring in a particular field. This result continues to be significant at the 1% level.

One potential concern about these last tests is that the measure of familiarity used in columns [1] and [2] may be endogenous to the choice of major or intended major. Specifically, a student may only become familiar with the earnings of a particular major after having chosen that major. To address this concern, columns [3] and [4] of Appendix Table 3 present the results of a similar analysis where familiarity is based on the survey question that asks respondents if they have family or a close acquaintance in a particular major field. Though one's familiarity rating may improve as they learn more about an intended major, it is less likely that their choice could have influenced their family members or close acquaintances. Consistent with our earlier results, we see that a respondent who has a family member or close acquaintance in a field is 5.7% to 6.1% more likely to major in (or report that they intend to major in) that field. The qualitative results for difficulty and employment prospects remain similar to those from the previous specification: difficulty remains largely unrelated (either statistically or economically, or both) to major choice, while an improvement in employment prospects is positively related to major choice.

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Table 1: Assumed Wage Distribution for Each Type of Major

	Income at the 75th percentile	Income at the median	Income at the 25th percentile	Unemployment income
Biology	\$117,000	\$65,000	\$38,000	\$14,000
Business	\$96,000	\$60,000	\$36,000	\$14,000
Education	\$64,000	\$47,000	\$32,000	\$14,000
Engineering	\$120,000	\$85,000	\$55,000	\$14,000
Health	\$90,000	\$62,000	\$43,000	\$14,000
Humanities	\$75,000	\$47,500	\$27,000	\$14,000
Law and public policy	\$76,000	\$50,000	\$30,000	\$14,000
Mathematics and computer science	\$106,000	\$75,000	\$46,000	\$14,000
Physical science	\$118,500	\$72,000	\$40,000	\$14,000
Psychology	\$72,000	\$48,000	\$30,000	\$14,000
Social science	\$60,000	\$35,000	\$14,000	\$14,000

Source: American Community Survey and unemployment income estimate based on Shimer (2005)

Table 2: Assumed Probability Distribution Over Wages for Each Type of Major

	Probability:			
	75th percentile	Median	25th percentile	Unemployed
Biology	0.2435	0.4870	0.2435	0.0259
Business	0.2398	0.4796	0.2398	0.0408
Education	0.2448	0.4896	0.2448	0.0207
Engineering	0.2420	0.4839	0.2420	0.0321
Health	0.2447	0.4895	0.2447	0.0211
Humanities	0.2399	0.4798	0.2399	0.0404
Law and public policy	0.2374	0.4747	0.2374	0.0506
Mathematics and computer science	0.2404	0.4808	0.2404	0.0385
Physical science	0.2427	0.4854	0.2427	0.0291
Psychology	0.2399	0.4798	0.2399	0.0404
Social science	0.2398	0.4795	0.2398	0.0409

Source: American Community Survey

Table 3: Percentage of Students Choosing Each Major for Different Levels of θ

	No uncertainty ($\theta \to \infty$)	Little uncertainty ($\theta = 1$)	More uncertainty $\left(\theta = \frac{1}{2}\right)$	High uncertainty $\left(\theta = \frac{1}{10}\right)$
Biology	9.48%	7.98%	10.2%	12.97%
Business	2.07%	2%	2.65%	4.96%
Education	0.03%	0.13%	1.07%	17.89%
Engineering	46.65%	46.47%	35.54%	9.41%
Health	4.85%	9.44%	21.33%	15.23%
Humanities	0.01%	0.01%	0.05%	5.82%
Law and public policy	0.05%	0.11%	0.2%	3.61%
Mathematics and computer science	18.7%	17.4%	12.09%	8%
Physical science	15.71%	14.65	14.32%	11.04%
Psychology	0.02%	0.1%	0.31%	6.83%
Social science	2.43%	1.7%	2.26%	4.23%

Table 4: List of Major Categories

Major area	Examples given to respondents (if any)
Biology and life science	Biology, Ecology, and Environmental Science
Business	Finance, Management, and Marketing
Education	
Engineering	Architecture and Mechanical Engineering
Health	Health Administration, Nursing, and Public Health
Humanities and arts	English, History, Languages, and Philosophy
Law and public policy	Pre-law and Public Administration
Mathematics and computer science	
Physical sciences	Chemistry, Geology, and Physics
Psychology and social work	
Social sciences	Economics, Political Science, and Sociology

Table 5: Respondents' Familiarity with Majors

Fields	Family or Close Acquaintances Mean	Family or Close Acquaintances S.D.	Familiarity with Earnings Mean	Familiarity with Earnings S.D.	Familiarity with Employment Prospects Mean	Familiarity with Employment Prospects S.D.
Biology	0.31	0.46	3.70	1.89	3.18	1.90
Business	0.64	0.48	3.99	1.69	3.92	1.85
Education	0.54	0.50	4.64	1.70	4.50	1.77
Engineering	0.43	0.50	4.09	1.87	4.33	1.96
Health	0.50	0.50	4.46	1.79	4.17	1.93
Humanities	0.38	0.49	3.42	1.58	2.82	1.60
Law	0.34	0.47	3.88	1.76	3.88	1.85
Math	0.34	0.48	3.66	1.68	3.21	1.82
Physical Sciences	0.27	0.44	3.55	1.71	2.90	1.73
Psychology	0.31	0.47	3.81	1.74	3.15	1.70
Social Sciences	0.32	0.47	3.44	1.65	2.85	1.63
Values	0 = No, 1= Yes		1=Not Familiar, 7=Extremely Familiar		1=Not Familiar, 7=Extremely Familiar	

Note: Summary statistics based on survey responses by college freshmen.

Table 6: Correlation between Familiarity Measures

	Family or Close Acquaintance	Familiarity with Earnings	Familiarity with Employment Prospects
Family or Close Acquaintance	1		
Familiarity with Earnings	0.249	1	
Familiarity with Employment Prospects	0.267	0.550	1

Table 7: Respondents' Average Salary Beliefs by Field

	All graduates in this field Mean	All graduates in this field S.D.	All graduates without advanced degrees Mean	All graduates without advanced degrees S.D.
Biology	73790	55613	54516	31300
Business	80934	47923	58944	28148
Education	46973	22958	38196	16711
Engineering	86397	42329	64975	33708
Health	76740	50976	54143	25450
Humanities	46673	25351	38186	19111
Law	85501	45842	56180	25028
Math	75720	51617	57825	34275
Physical Sciences	71789	51956	52532	21575
Psychology	54541	27708	43886	33717
Social Sciences	61582	43434	46210	22347

Note: Summary stats based on survey responses by college freshmen.

Table 8: Respondents' View of Majors

	Difficulty of Courses		Expected Employment Prospects	
Fields	Mean	S.D.	Mean	S.D.
Biology	4.96	1.09	4.74	1.44
Business	3.96	1.09	5.14	1.29
Education	3.22	1.05	4.20	1.40
Engineering	5.56	1.05	5.62	1.37
Health	4.84	1.27	5.41	1.34
Humanities	3.43	1.30	2.86	1.33
Law	4.96	1.09	4.60	1.32
Math	5.34	1.11	5.27	1.33
Physical Sciences	5.33	1.18	4.57	1.35
Psychology	3.50	1.24	3.92	1.32
Social Sciences	3.81	1.26	3.86	1.31
Values	1=Very Easy, 7=Almost Impossible		1=Very Unlikely, 7=Very Likely	

Note: Summary statistics based on survey responses by college freshmen.

Table 9: Average Salaries by Field and the Effect of Uncertainty

	[1] OLS	[2] OLS with Fixed Effects
Familiarity with potential earnings (1 to 7)	0.048***	0.040***
	[11.517]	[11.075]
Gender	0.042***	
	[2.745]	
Age	-0.027***	
	[-2.745]	
Race: Black	-0.041	
	[-0.968]	
Race: Asian	-0.073***	
	[-2.802]	
Race: Latino	0.017	
	[0.305]	
Race: Other	0.001	
	[0.024]	
Receives financial aid	-0.078***	
	[-5.017]	
Field: Biology	0.162***	0.165***
	[4.623]	[7.479]
Field: Business	0.235***	0.244***
	[6.665]	[10.919]
Field: Education	-0.302***	-0.289***
	[-8.455]	[-12.661]
Field: Engineering	0.314***	0.326***
	[8.823]	[14.387]
Field: Health	0.156***	0.167***
	[4.410]	[7.419]
Field: Humanities	-0.254***	-0.254***
	[-7.247]	[-11.553]
Field: Law	0.303***	0.311***
	[8.582]	[13.949]
Field: Mathematics	0.198***	0.201***
	[5.655]	[9.130]
Field: Physical Sciences	0.156***	0.157***
	[4.461]	[7.128]
Field: Psychology	-0.107***	-0.105***
	[-3.061]	[-4.763]
Constant	11.296***	10.782***
	[61.324]	[578.178]
R2	0.214	0.395
Observations	3,641	3,641

t-statistics in parenthesis. * p<0.1; ** p<0.05; *** p<0.01.

Note 1: Dependent variable is log estimated average salary. Excluded field is social sciences.

Note 2: Results are based on data from survey responses by college freshmen.

Table 10: Familiarity Differences by Gender

	Reported Values			Deviations		
	Male	Female	t-stat	Male	Female	t-stat
Biology	3.08	3.26	0.87	-0.38	-0.13	2.33**
Business	4.03	3.81	-1.11	0.31	0.20	-1.08
Education	4.60	4.45	-0.79	0.78	0.79	0.14
Engineering	4.48	4.20	-1.31	0.62	0.51	-1.08
Health	4.08	4.26	0.89	0.30	0.55	2.52**
Humanities	2.78	2.87	0.52	-0.60	-0.49	1.17
Law	3.88	3.89	0.04	0.19	0.30	1.10
Math	3.41	3.09	-1.60	-0.16	-0.27	-1.15
Physical Sciences	3.19	2.70	-2.56**	-0.30	-0.59	-3.48***
Psychology	3.06	3.23	0.89	-0.38	-0.22	1.68*
Social Sciences	3.10	2.66	-2.47**	-0.38	-0.64	-2.97***
Obs	145	193		130	173	

* p<0.1; ** p<0.05; *** p<0.01.

Note 1: Deviations based on individual means and standard deviations of familiarity responses to all majors. Those with no deviations in their responses across major are not included in the "Deviations" section above.

Note 2: Summary statistics based on survey responses by college freshmen.

Appendix Table 1: Average Salaries by Field and the Effect of Uncertainty if Limited to No Advanced Degrees

	[1] OLS	[2] OLS with Fixed Effects
Familiarity with potential earnings (1 to 7)	0.044*** [10.517]	0.036*** [10.195]
Gender	0.070*** [4.623]	
Age	-0.029*** [-2.893]	
Race: Black	-0.088** [-2.103]	
Race: Asian	0.001 [0.035]	
Race: Latino	-0.151*** [-2.679]	
Race: Other	0.044 [1.091]	
Receives financial aid	-0.066*** [-4.233]	
Field: Biology	0.144*** [4.109]	0.146*** [6.830]
Field: Business	0.195*** [5.555]	0.204*** [9.395]
Field: Education	-0.250*** [-7.019]	-0.237*** [-10.683]
Field: Engineering	0.270*** [7.604]	0.281*** [12.786]
Field: Health	0.091*** [2.587]	0.102*** [4.658]
Field: Humanities	-0.213*** [-6.095]	-0.213*** [-9.966]
Field: Law	0.154*** [4.379]	0.162*** [7.482]
Field: Mathematics	0.201*** [5.749]	0.204*** [9.516]
Field: Physical Sciences	0.141*** [4.045]	0.142*** [6.630]
Field: Psychology	-0.093*** [-2.655]	-0.090*** [-4.223]
Constant	11.057*** [60.259]	10.542*** [581.985]
R2	0.161	0.315
Observations	3,641	3,641

t-statistics in parenthesis. * p<0.1; ** p<0.05; *** p<0.01.

Note 1: Dependent variable is log estimated average salary for individuals with no advanced degrees. Excluded field is social sciences.

Note 2: Results are based on data from survey responses by college freshmen.

Appendix Table 2: Summary Statistics by Choice of Major or Intended Major

	Familiarity with earnings			Difficulty of Courses	Job Prospects	
	Own Major	All other majors	Rank of Own Major	Rank of Own Major	Rank of Own Major	Number of Majors
All Fields	4.55	3.44	2.71	4.11	3.60	340
Biology	4.96	3.94	2.60	2.94	2.49	47
Business	4.57	2.93	1.54	5.46	2.68	28
Education	5.00	2.60	1.00	7.50	3.00	2
Engineering	5.94	3.10	1.10	1.92	1.12	52
Health	5.86	3.69	1.61	2.54	1.86	28
Humanities	3.03	3.27	4.69	6.31	7.97	32
Law	5.29	3.43	1.14	2.86	3.00	7
Math	4.11	2.86	2.05	2.68	2.16	19
Psychology	4.42	4.22	4.08	2.38	3.27	26
Physical Sciences	4.33	3.42	2.85	6.28	4.79	39
Social Sciences	3.43	3.42	3.97	5.67	5.45	60

Note 1: Ratings are on a scale of 1 to 7 and ranks 1 to 11.

Note 2: Summary statistics based on survey responses by college freshmen.

Appendix Table 3: Measuring the Impact of Familiarity on the Probability of Choosing a Major

	[1]	[2]	[3]	[4]
	Familiarity with Earnings		Family or Close Acquaintance in Field	
	Rating	Rank	Rating	Rank
Familiarity with potential earnings (1 to 7)	0.025***			
	[9.478]			
Rank of familiarity with potential earnings (1 to 11)		-0.018***		
		[-9.677]		
Family or Close Acquaintance in Field			0.057***	0.061***
			[5.734]	[6.066]
Difficulty of courses (1 to 7)	0.006		0.006	
	[1.431]		[1.560]	
Rank of difficulty in courses (1 to 11)		-0.002		-0.004**
		[-1.236]		[-2.030]
Likelihood of employment if major in field (1 to 7)	0.023***		0.032***	
	[6.007]		[8.575]	
Rank of likelihood of employment if major in field (1 to 11)		-0.011***		-0.014***
		[-5.785]		[-7.869]
Observations	3,740	3,740	3,740	3,740

t-statistics in parenthesis. * p<0.1; ** p<0.05; *** p<0.01.

Note 1: Coefficients presented are the mean marginal effects of a probit where the dependent variable is whether a respondent intends to major in the field they are evaluating. Field indicator variables are included in all specifications.

Note 2: Analysis results are based on data from survey responses by college freshmen.