How Do College Students Form Expectations?*

Basit Zafar

Abstract

This paper focuses on how college students form expectations about various major-specific outcomes. For this purpose, I collect a panel dataset of Northwestern University undergraduates that contains their subjective expectations about major-specific outcomes. Though students tend to be overconfident about their future academic performance, they revise their expectations in expected ways. The updating process is found to be consistent with a Bayesian learning model. I show that learning plays a role in the decision to switch majors, and that major switchers respond to information from their own major. I also present evidence that learning is general and not entirely major-specific.

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1 Introduction

Schooling choices are made under uncertainty–uncertainty about personal tastes, individual abilities, and realizations of choice-related outcomes. Although some theoretical work incorporates the uncertainty associated with schooling choices (Manski, 1989; Altonji, 1993; Malamud, 2007), there is little empirical work in this area (exceptions include Bamberger, 1986; Arcidiacono, 2004; Cunha, Heckman, and Navarro, 2004; Stange, 2008). Moreover, existing empirical studies make non-verifiable assumptions on expectations, assume individuals are rational and form expectations in the same way, and use choice data to infer decision rules conditional on the maintained assumptions about expectations. This approach is problematic for several reasons. First, observed choices may be consistent with several combinations of expectations and preferences (Manski, 1993). Second, the information-processing rule has varied considerably among studies of schooling behavior, and it's not clear which is the correct one to use (given that individuals may use idiosyncratic rules to form their beliefs). A solution to this identification problem is to directly elicit subjective beliefs (Manski, 2004) and incorporate them into choice models (Delavande, 2008a; Zafar, 2008). However, to predict behavior in a new scenario that could possibly affect expectations in nonobvious ways, one would need to understand the process of expectations formation. Moreover, once education is treated as a sequential choice, it is clear that understanding how students perceive and resolve uncertainty about (pecuniary and non-pecuniary) returns to a choice is a prerequisite for informed analysis of schooling decisions. Because few studies collect data on subjective beliefs, and even fewer follow the same respondents over time, little is known about how students form expectations and resolve uncertainty in the context of schooling choices. The main goal of this paper is to fill this gap in the literature.

This paper examines how and why college students revise their expectations about outcomes related to choice of major. For this purpose, I designed and conducted two surveys that elicited subjective expectations from Northwestern University undergraduates regarding their choice of major. The first survey, administered to students in the early part of their sophomore year, collected details on students' demographics and subjective beliefs about major-specific outcomes; these data were used to estimate a choice model of college majors (Zafar, 2008). The second survey, conducted about a year after the first, collected data on how individuals revise their beliefs for major-specific outcomes. Both surveys elicited the respondents' beliefs about outcomes for their own major, as well as for some other majors in their choice set. Since understanding the mechanisms that lead individuals to revise their beliefs also requires data that directly identify new information, the surveys also contained questions that identified *some* of the new information about their academic ability that individuals had acquired between the two surveys. The major-specific outcomes for which beliefs were elicited include both outcomes realized in college and those realized in the workplace. Examples of the former include graduating in 4 years, enjoying the coursework, and having parents approve of the choice, while examples of the latter include outcomes like finding a job upon graduation and earnings at the jobs. While some of these outcomes are binary (for example, a student either graduates in 4 years or not), others such as earnings are continuous. The data are described in Section 2.

Section 3 of the paper analyzes how and why students update their beliefs. Analysis of the panel on beliefs shows that students, in response to new information, modify their beliefs systematically and somewhat rationally. This finding matches with conclusions reached in Bernheim (1988), Dominitz (1998), Smith et al. (2001), Hurd and McGarry (2002), and Lochner (2007), all of whom find that expectations are responsive to new information. However, existing studies, due to lack of data that identify new information, cannot pin down the causal explanation for the revision in expectations without making some assumptions either on the prior expectations or on how to interpret changes in the environment.[1] This paper uses a more direction measure of new information. In order to understand the mechanisms that lead to revision of beliefs, the first survey elicited beliefs of future GPA over a horizon of one year; these GPA realizations were observed at the time of the second survey. Comparing the beliefs with actual realizations of GPA allows me to develop an "information metric" that identifies some new information about their own unobserved academic ability that students learn between the two surveys. Based on beliefs reported in the first survey, I find that students, on average, tend to be overconfident about their future academic performance. However, they adjust their beliefs in response to the new information appropriately. Using local linear regressions, I find that students who receive positive information revise upward their predictions of short-term future GPA only if the information content is very positive, and similarly those who receive

[1] Though some laboratory and field experiments have studied how agents update their beliefs with new information (Viscusi and O'Connor, 1984; El-Gamal and Grether, 1995; Delavande, 2008b; and Houser, Keane, and McCabe, 2004), these studies use extremely stylized settings and focus on learning over short time horizons. It is yet to be seen whether their results would be evident in less standardized environments or over longer time periods.

negative information revise their predictions downward only if the information content is very negative. Students who receive information that is in the intermediate range don't revise their short-term GPA beliefs. Moreover, no effect is found on long-term GPA expectations. I also find a negative relationship between the information metric and revisions in beliefs about number of hours per week that students expect to spend on coursework. This result suggests that students view ability and effort as substitutes in the production of their achievement, which is consistent with Stinebrickner and Stinebrickner (2007), who find a causal effect of studying on academic performance. I do not find a systematic relationship between the information metric and revisions in beliefs for outcomes associated with the workplace.

Since I collect data on revisions in beliefs for outcomes associated with the respondent's current major as well as a some other majors in the respondent's choice set, I can also address the question of whether learning is general or major-specific.[2] Similar patterns of belief-updating are observed for the various binary outcomes across the different major categories. Section 3 shows that the extent to which respondents resolve their uncertainty for the various binary outcomes is similar across both own major as well as other major categories. In response to new information, students also revise their beliefs about academic ability and expected coursework hours per week for these other major categories in a meaningful way. In particular, I cannot reject the null that belief-updating and resolution of uncertainty for the various outcomes is similar across pursued as well as non-pursued majors. These results suggest that, besides having a major-specific component, learning also has a general component: By leaning about match-quality in one's own major, students are acquiring information not only in their current major, but also in other majors.[3] In that sense, the results are in line with more recent models of labor market learning where learning has both a match-specific component as well a general one (Gorry, 2010; Papageorgiou, 2010).

I do not estimate a specific model of learning in this paper. There are at least two reasons for this: (1) the analysis shows heterogeneity in information-processing rules employed by students, and hence testing a particular learning model is not very useful, and (2) the purpose of collecting

[2]There is a well-developed literature on learning in the labor market. On one extreme, there are models where learning is match specific (Jovanovic, 1970), and on the other extreme where learning is general (Farber and Gibbons, 1996).

[3]However, I do not have data on revisions in beliefs for majors in the respondent's choice set that are neither the more preferred or least preferred majors, i.e., majors for which the respondent has not developed strong feelings and for which presumably little information is received between the two surveys. The results about learning being general may not extend to such major categories.

subjective data is to relax assumptions on expectations formation, and estimating a model of learning somewhat defeats this purpose. However, in Section 4, I test whether students use Bayesian-updating— the most common model used in empirical work—when revising beliefs for binary outcomes. I find that individuals who are more uncertain about the major-specific outcomes in the initial survey make greater absolute revisions in their beliefs. In terms of the revision process, the prior belief (i.e., belief reported in the first survey) is significant for almost all outcomes and information metric is significant for more than half of the outcomes. I also find that the information metric is relatively less useful in explaining the updating for beliefs in non-pursued majors. Given that the information metric is a measure of the extent of learning about unobserved ability in pursued majors, this finding should not be surprising. These results are broadly consistent with a Bayesian learning model.

Over time, students may change their schooling choices (drop out of college or change their field of study) as they learn about their ability, tastes, and quality of match. Dropouts are rare in the current setting: 93% of Northwestern University undergraduate students graduate with a degree within five years of first enrolling. Instead, the phenomenon of switching majors is more common: 12% of the students in my sample switch majors between the two surveys.[4] The analysis in Section 5 suggests that learning plays a role in the decision to switch majors. While I don't find a significant role for the information metric or realized GPA changes in the decision to switch majors, there is evidence that negative revisions in beliefs about graduating in 4 years, enjoying coursework, and expected salary are associated with dropping a major. Analysis of the initial beliefs of major switchers reveals that they tend to have optimistic beliefs of outcomes in the original major relative to individuals who don't switch majors, but similar beliefs for alternative majors. This suggests that students who switch majors are primarily responding to information in their own major.

Bulk of the analysis in the paper on learning and belief-updating focuses on binary outcomes. This is because only the expected value was elicited for continuous outcomes (such as future earnings, coursework hours per week), and knowledge of the distribution would be needed to conduct any thorough analysis. To understand how students revise their beliefs about continuous outcomes, Section 6 focuses on whether students' predictions of earnings become more

[4]Switching of majors is a common occurrence in other settings as well. For example, Arcidiacono (2004) finds that 18% of the students in the NLS72 who attend college switch majors. Similarly, Altonji (1993) documents the discrepancy between planned majors and actual majors.

accurate over time.[5] Since no objective data exist with which students' own expected major-conditional income can be compared, I instead analyze how students' predictions of starting salaries of recent graduates evolve over time. The advantage of this approach is that earnings data exist for these recent graduates. The analysis reveals that while students' prediction errors get smaller over time, it is only prediction errors in own major that get smaller. Prediction errors in non-pursued continue to stay the same, with students primarily underestimating salaries in non-pursued majors.

This paper adds to the expanding literature on subjective expectations, and makes at least three contributions. First, it is one of the few studies that analyzes how students form and update expectations about educational choices. The only other study in this regard is Stinebrickner and Stinebrickner (2008), who use a panel of subjective beliefs about academic ability from low-income college students, and study how students update their beliefs about grades and how these beliefs affect their college drop-out decision. While they have better and higher frequency to address the question of learning about grades, the current study focuses on learning for a broad set of outcomes, uses a more direct measure of information, makes arguably fewer assumptions, and also sheds light on the process of learning in counterfactual majors. The second point of departure of the paper relative to existing literature is that new information is directly backed out from changes in expectations, instead of imposing assumptions on the link between the environment and private information available to the decision-maker, as is the norm in the literature.[6] Third, since I collect data on revisions in beliefs for pursued majors as well as counterfactual choices, I can shed light on how learning in pursued majors differs from non-pursued majors. The question of general versus specific learning is something that has only been studied in the context of labor market learning, and remains unexplored in the context of education because of the breadth of data required to asses this.

Finally, Section 7 of the paper concludes.

[5] Several cross-sectional studies have elicited subjective expectations about monetary returns in the context of higher education: Freeman (1971), Smith and Powell (1990), Blau and Ferber (1991), Betts (1996), and Dominitz and Manski (1996).

[6] Longitudinal studies of subjective data include Bernheim (1988), Dominitz (1998), Smith et al. (2001), Benitez-Silva and Dwyer (2005), Lochner (2007), who analyze revisions to expectations of social security benefits, earnings, longevity, retirement, and arrest, respectively. These studies either are unable to infer the information content of changes in the environment and hence cannot analyze the role of new information, or make assumptions on the relationship between the information available at different points in time to study updating.

2 Data

The data used in this study come from two surveys that were administered to a sample of students in Northwestern University's undergraduate class of 2009. The first survey was administered to students in the early part of their sophomore year over the period from November 2006 to February 2007. I denote this as the *Fall 2006* or *initial* survey for the empirical analysis. Since Northwestern University requires students to officially declare their majors by the beginning of their junior year, the timing of the initial survey corresponds to the period when students are actively thinking about which major to choose. The second survey was administered to a subset of the initial survey-takers at the beginning of their junior year, when students had presumably settled on their final majors.[7] The survey spanned the period from November 2007 to February 2008. I denote it as the *Fall 2007* or *follow-up* survey.

Respondents for the initial survey were recruited by flyers posted around campus and by e-mailing a sample of eligible sophomores whose e-mail addresses were provided by the Northwestern Office of the Registrar. Prospective participants were told that the survey was about the choice of college majors and that they would receive $10 for completing the 45-minute electronic survey. Respondents were required to come to the Kellogg Experimental Laboratory to take the electronic survey.

A total of 161 sophomores took the first survey, 92 of whom were females. The 45-minute survey consisted of three parts. The first part collected demographic and background information (including parents' and siblings' occupations and college majors, source of college funding, etc.). The second part collected data relevant for the estimation of the choice model (see Zafar, 2008). The third part collected beliefs about future GPA at different time horizons. At the end of the survey, respondents were asked if they were willing to participate in a follow-up survey in a year's time.

Of the 161 respondents who took the initial survey, 156 agreed to be contacted for the follow-up. About a year after the first survey, individuals who gave their consent were contacted by e-mail for the follow-up; the e-mail summarized the findings of the initial survey and the purpose of the follow-up. Students were told that they would be compensated $15 for the 1-hour electronic survey. The follow-up was administered in the PC Laboratory located in the

[7] Students can still change their major during their junior or senior year, but they have to go through a formal process to do so.

Northwestern Main Library.

Of the 156 initial survey respondents, 117 (75%) took the follow-up survey. The first column of Table 1 shows the characteristics of individuals who took the follow-up survey. For comparison, characteristics of the initial sample and the actual sophomore population are shown in columns (2) and (3), respectively. Respondents to the follow-up survey seem similar to the initial survey respondents in most aspects. Even though the average GPA of follow-up respondents is higher than that of the initial survey-takers, the difference is not statistically significant. The bottom panel of Table 1 shows that the distribution of majors in the Weinberg College of Arts and Sciences (WCAS) for the students taking the two surveys is similar, suggesting no differential attrition by field of study. Students of Asian ethnicity are overrepresented in the survey samples (both in the initial and follow-up survey) relative to their population proportion. Survey-takers, especially males, have higher average GPAs than their population counterparts. However, for the purposes of this study, it's the selection into the follow-up survey that would be of concern. Based on observables, I don't find any selection in who decides to take the follow-up survey. To the extent that certain ethnicities are overrepresented in my sample relative to the underlying population, this should bias the results only if one believes that the process of belief updating and learning is differentially affected by these traits. Since my sample overrepresents Asians, for robustness purposes I repeat the analysis in the paper by excluding this group. The results do not change qualitatively.

The follow-up survey consisted of two parts. The first part focused on how individuals revise their beliefs about major-specific outcomes. While the initial survey elicited beliefs about outcomes associated with all majors in the individual's choice set (which could be 8 or 9 majors),[8] the follow-up survey elicited beliefs for major-specific outcomes for only three different major categories in the individual's choice set. Beliefs about the major-specific outcomes were elicited for: 1) the major that the individual was pursuing at the time of the follow-up survey (one's most preferred major or current major), 2) the individual's second major (or the second most preferred major at the time of the follow-up survey if the student did not have a second major), and 3) a major that the individual had once pursued but was no longer pursuing (if this was not applicable, beliefs were elicited for the least preferred major in the individual's choice set at the time of the follow-up survey). The second part of the survey collected data on the

[8]The College of Arts and Sciences at Northwestern University consists of 41 majors. Similar majors were pooled together. Table A1 in the Appendix shows the categorization of majors.

individuals' GPA at different points in the past, as well as their beliefs about their academic performance at different points in the future. Individuals were also requested to upload their transcripts; only 41 respondents (35%) permitted access to their transcript data, and hence these data are not used in the analysis.

The set of major-specific outcomes for which beliefs were elicited can be classified as outcomes realized in college, denoted by the vector **a**, and outcomes realized in the workplace, denoted by the vector **c**. The vector **a** includes the outcomes:

a_1 successfully completing (graduating) a field of study in 4 years

a_2 graduating with a GPA of at least 3.5 in the field of study[9]

a_3 enjoying the coursework

a_4 hours per week spent on the coursework

a_5 parents approve of the major

while the vector **c** consists of:

c_1 obtain an acceptable job immediately upon graduation

c_2 enjoy working at the jobs available after graduation

c_3 are able to reconcile work and family while at the available jobs

c_4 hours per week spent working at the available jobs

c_5 social status of the available jobs

c_6 income at the available jobs

Note that $\{a_r\}_{r=\{1,2,3,5\}}$ and $\{c_q\}_{q=\{1,2,3\}}$ are binary, while outcomes a_4 and $\{c_q\}_{q=\{4,5,6\}}$ are continuous.[10] The survey elicited the probability of the occurrence of the binary outcomes, i.e., $P_{ikt}(a_r = 1)$ for $r = \{1, 2, 3, 5\}$ and $P_{ikt}(c_q = 1)$ for $q = \{1, 2, 3\}$. Expected value was elicited for the continuous outcomes, i.e., $E_{ikt}(a_4)$ and $E_{ikt}(c_q)$ for $q = \{4, 6\}$. As mentioned earlier, the initial survey elicited these beliefs for *all* majors in the individual's choice set, while the follow-up survey elicited them for three different major categories in the individual's choice set.

Questions eliciting the subjective probabilities of major-specific outcomes were based on the use of percentages. An advantage of asking probabilistic questions relative to approaches

[9]This outcome is meant to capture the student's belief about academic ability in a major. The cutoff of 3.5 for graduating GPA was arbitrary.

[10]Social status of available jobs, c_5, was elicited as an ordinal ranking. In hindsight, this question should have been asked in terms of the probabilistic chance of obtaining a high-status job, since the ordinal ranking does not reveal the respondent's uncertainty about the outcome.

that employ a Likert scale or a simple binary response (yes/no or true/false) is that responses are interpersonally comparable and allow the respondent to express uncertainty (see Manski, 2004, for an overview of the literature on subjective expectations). As is standard in studies that collect subjective data, a short introduction was read and handed to the respondents at the start of the survey. The wording of the introduction was similar to that in Delavande (2008a). An excerpt of the survey containing the introduction and list of questions dealing with the major-specific outcomes is presented in the Appendix. The full survey questionnaire is available on request from the author.

It would be impossible to describe patterns in the responses for all outcomes. Table 2 presents only the subjective belief distributions reported in both surveys for graduating with a GPA of at least 3.5 in one's current major and one's least preferred major. The table shows that respondents use the entire scale from zero to 100, and that there is substantial heterogeneity in beliefs. Respondents tend to round off their responses to the nearest 5, especially for answers not at the extremes. There is a concern that respondents might answer 50% when they want to respond to the interviewer, but are unable to make any reasonable probability assessment of the relevant question (Bruine de Bruin et al., 2000). However, the 50% response is not the most frequent one in the majority of the cases. Over time, it seems that individuals tend to revise downward their beliefs for graduating with a GPA of at least 3.5 for both their current major as well as their least preferred major. For example, in the initial survey, nearly half of the respondents believed there was a greater than 80% chance of graduating with a GPA of at least 3.5 in their current major. In the follow-up survey, the fraction of respondents who believed that to be the case had dropped to about 30%. The next section explores how students revise their beliefs.

3 Belief-updating and Learning

One way to understand the process of how individuals form expectations is to study how expectations are revised in response to new information. This area remains relatively unexplored because studying this question requires following individuals over time and obtaining data that directly identify new information. Studies have found that expectations tend to be responsive to changes in the environment but, without making some assumptions, they cannot determine the causality since the data do not directly identify the new information.[11] These studies either assume that the changes in the environment were totally unanticipated and interpret the change as new information (for example, the analysis in Hurd and McGarry, 2002, treats the onset of cancer or the death of one's spouse as totally unpredictable), or invoke a variety of assumptions on prior expectations to identify new information (an approach used by Bernheim, 1988). Either way, existing studies impose a link between the new information and current information available to the decision-maker. This paper directly backs out the new information from changes in elicited expectations. The survey questionnaires included questions intended to identify changes in the student's information set. Using responses to these questions, this section analyzes how students revise their beliefs.

This section also tests for whether there are systematic differences in how students revise their beliefs for outcomes in different majors. Several tests are conducted to determine the extent of learning, i.e., whether students only learn about and revise outcomes for their own major (*major-specific* learning), or also learn about outcomes in other majors (*general* learning).

I first describe some patterns in students' revisions. Table 3 regresses the change in beliefs between the two surveys for each outcome onto dummies for the different major categories (second preferred major, second major, dropped major, and least preferred major). The coefficients show the direction and magnitude of the mean change in beliefs about the various outcomes for each of the majors. Mean changes in the current major are indicated in the estimate of the constant. The estimate of the constant term shows significant negative revisions between the two surveys in student beliefs for graduating with a GPA of at least 3.5, enjoying coursework, expected coursework hours per week, enjoying work at the jobs, and positive revisions in beliefs of expected salary at age 30.

Results of two F-tests are also reported in each column of Table 3. The purpose of the first F-test is to determine whether revisions for beliefs associated with majors excluding the current major are different from those in current major; therefore, it tests for the joint significance of the covariates excluding the constant term. With the exception of revisions in beliefs about expected coursework hours per week, the null that the covariates are not jointly different from

[11] For example, Dominitz (1998) finds that revisions to expectations of future earnings are associated with earnings that respondents realize between interviews. Smith et al. (2001) find that HRS respondents revise their longevity expectations sensibly in response to health shocks. Hurd and McGarry (2002) find that individuals revise their survival probabilities downward in response to the onset of cancer or the death of one's spouse. Lochner (2007) finds that individuals revise their arrest probabilities downward if, for example, a sibling engages in a crime.

zero cannot be rejected for any outcome. The second F-test checks if revisions for beliefs associated with majors that an individual never pursued (the least preferred major and second preferred major) are different from those for the current major. The null of similar revisions as for the current major can only be rejected for beliefs about expected coursework hours per week and for expected salary at age 30.

The results in Table 3 suggest that revisions are of similar nature across the different major categories. This raises the question of whether learning is general or major-specific. To address this, I analyze how the beliefs for the binary outcomes (elicited on a scale of 0-100) move towards the extremities.[12] For this purpose, I define:

$$S_{im}^{b_j} = \begin{cases} 1 \text{ if } (10 < \; P_{im,t}(b_j = 1) \; < 90) \; \& \; (P_{im,t+1}(b_j = 1) \; \leq 10 \mid P_{im,t+1}(b_j = 1) \; \geq 90) \\ 0 \text{ otherwise.} \end{cases},$$

i.e., the indicator variable, $S_{im}^{b_j}$ equals one if respondent i's belief for outcome b_j in major m moves from the non-extremities (between 10-90) in the initial survey to the extremities (defined as a response of ≤ 10 or ≥ 90) in the follow-up survey.[13] In Table 4, this indicator is regressed onto a constant term and dummies for the different major categories (second preferred major, second major, dropped major, and least preferred major) for each of the binary outcomes. The coefficient on the constant term shows that beliefs for all outcomes associated with one's current major move into the extremities for a significant fraction of respondents. For example, in the case of parents' approval for one's own major, beliefs of 19% of the respondents move into the extremities, while beliefs for 11% of the respondents move into the extremities for graduating in 4 years in one's current major. If learning were major-specific, one would expect coefficients on the various major dummies to be significantly different from zero. That is, however, not the case for most outcomes. A strict test for general learning versus major-specific learning would be that the coefficients on the second preferred major and the least preferred major (both major categories containing majors never pursued by the respondent) are not statistically different from zero. The F-test for the joint significance of the least preferred major and second preferred major dummies tests for this precisely. With the exception of beliefs about work flexibility, I fail

[12]Since only the expected value (and not the distribution) was elicited for the continuous outcomes, whether learning is general or specific for continuous outcomes cannot be tested.

[13]The analysis yields qualitatively similar results if extremities are instead defined as a response of ≤ 5 or ≥ 95 on a 0-100 scale.

to reject the null that learning (here defined as beliefs moving into the extremities) is general.

It should be pointed out that the data I collect contain revisions in beliefs for one's own major, second (preferred) major, and least preferred or dropped major – all major categories that the respondent has developed strong feelings about. I do not observe revisions in beliefs for majors that were neither the most or least preferred ones. Individuals are likely to learn the least about such majors. Therefore, while I cannot reject the null that learning is general for the different major categories that I have data on, the result may not hold for major categories that students learned the least about (that is, majors that were neither the least or most preferred).

3.1 Revisions of GPA beliefs

I next outline a simple model of belief updating. Let X_{it} be individual i's expectation at time t about the value of a variable $\mathbf{X}$ that would be realized at some point in the future. Moreover, let Ω_{it} denote i's information set at time t. For simplicity, I assume that $\mathbf{X}$ is a binary event so that:

$$X_{it} = E(\mathbf{X}|\Omega_{it}) = \Pr(\mathbf{X} = 1|\Omega_{it}).$$

Similarly, X_{it+1} is i's expectation about the value of $\mathbf{X}$ at time $t+1$. Individuals are assumed to use all available information in forming expectations; therefore, revisions of expectations are determined solely by new information. I further assume that, at time $t+1$, the individual has access to all information that was available at time t. Therefore, $\Omega_{it+1} = (\Omega_{it},\, \omega_{it+1})$, where ω_{it+1} is *new* information that becomes available to i between time t and $t+1$. It follows that

$$E(X_{it+1}|\Omega_{it}) = E[E(\mathbf{X}|\Omega_{it}, \omega_{it+1})|\Omega_{it}] = E(\mathbf{X}|\Omega_{it}) = X_{it},$$

which implies that

$$\Pr(\mathbf{X} = 1|\Omega_{it+1}) = \Pr(\mathbf{X} = 1|\Omega_{it}) + \varepsilon_{it+1}, \tag{1}$$

where $E(\varepsilon_{it+1}|\Omega_{it}) = 0$, i.e., ε_{it+1} is a function of new information that becomes available after time t. Equation (1) states that the change in expectations between time t and $t+1$ about some event $\mathbf{X}$ that is realized at some point in the future is a function of new information that becomes available after time t.

In the context of this study, period t refers to the first survey, Fall 2006, and period $t+1$ refers to the follow-up survey, Fall 2007 (see Figure 1 for a visual depiction of the timeline). $\mathbf{X} = 1$ refers to the binary event that the *semester-specific* GPA at the end of Spring 2008

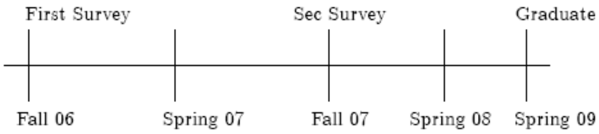

Figure 1: Timeline

(which is realized after the individual takes the follow-up survey) is above a certain threshold. In this case, the threshold is the individual's GPA at the time of the initial survey, so $\Pr(\mathbf{X} = 1|\Omega_{it}) = \Pr(\text{Spring 2008 GPA}_i > \text{Fall 2006 GPA}_i|\Omega_{it})$, where Fall 2006 GPA_i is individual i's cumulative GPA at the time of the initial survey.[14] So $\Pr(\mathbf{X} = 1|\Omega_{it+1}) - \Pr(\mathbf{X} = 1|\Omega_{it})$ is the change in i's subjective belief between the Fall 2006 and Fall 2007 surveys about her semester-specific Spring 2008 GPA being above her cumulative Fall 2006 GPA.

Panel A of Figure 2 depicts the local linear regression estimates of the change in Spring 2008 GPA beliefs on the change in the individual's GPA between the two surveys.[15] The figure also presents the distribution of realized GPA change between the two surveys. Individuals experience GPA changes that vary in the range of -0.45 to 0.4, with -0.01 being the mean. Revisions of Spring 2008 GPA expectations seem to be positively related to changes in realized GPA. The change in beliefs about Spring 2008 GPA in response to positive and negative changes in realized GPA is almost symmetric, except for very negative GPA changes. Panel B of Figure 2 depicts the local linear regression estimates of the change in *cumulative* Graduating GPA beliefs on changes in realized GPA between the two surveys. Both surveys elicited the individuals' beliefs about their cumulative GPA at graduation in their major being above 3.5; the dependent variable is now the change in this belief.[16] As depicted in panel B, individuals revise their belief of graduating GPA downward in response to negative changes in realized GPA, but do not revise upward their belief of graduating GPA in response to positive changes in realized GPA.

Similar responsiveness of Spring 2008 GPA beliefs to positive and negative changes in realized GPA may lead one to conclude that increases and decreases in realized GPA between the two surveys contained equally useful information. However, to be able to conclude this, one needs to discern the information content of the GPA realized at the beginning of Fall 2007.

[14] Depending on when the individual took the initial survey, Fall 2006 GPA_i refers to the individual's GPA at the *beginning* of Fall 2006 or at the *end* of Fall 2006.

[15] I use a local linear regression estimator instead of a Kernel regression since this avoids the boundary problem. I experimented with different bandwidths, but the figures did not change much.

[16] Here, $\Pr(\mathbf{X} = 1|\Omega_{it}) = \Pr(\text{Graduation GPA}_i \geq 3.5|\Omega_{it})$. This threshold, unlike the case for the Spring 2008 GPA belief, is not individual specific.

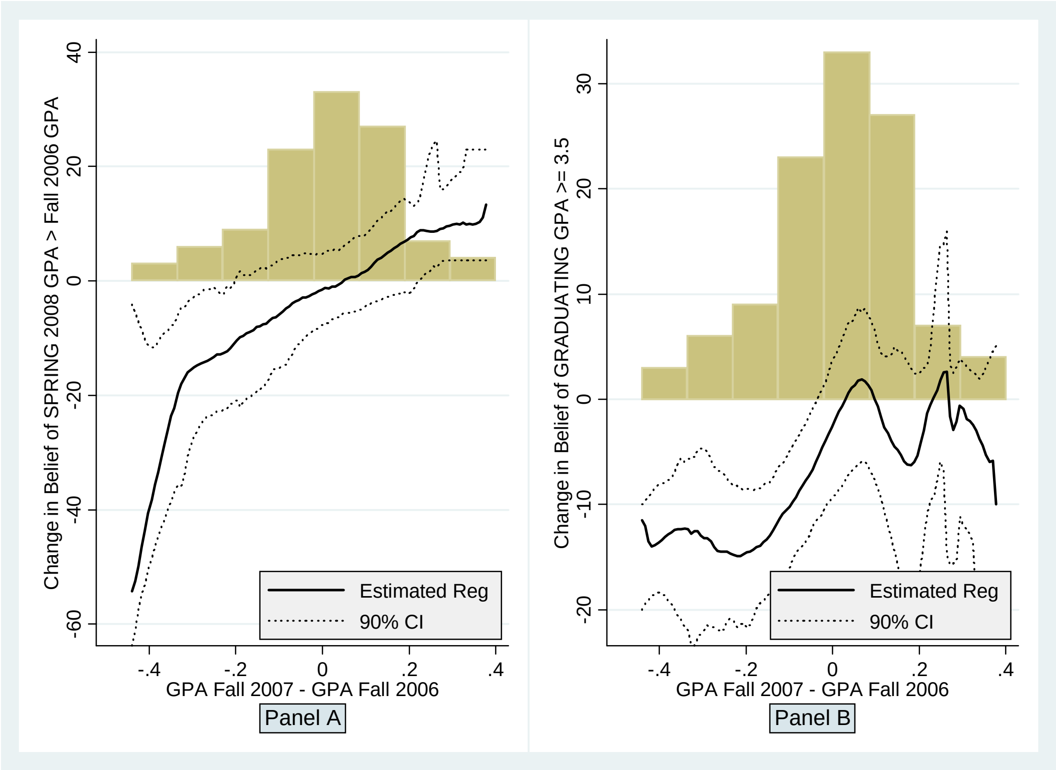

Figure 2: Local linear regressions of the change in Spring 2008 beliefs (Panel A) and Graduation GPA beliefs (Panel B) on changes in GPA between the surveys. Confidence intervals estimated from 200 bootstrap sampling distributions.

Students may expect their GPA to tend over time for several reasons: For example, a student anticipating more difficult upper level courses will expect her GPA to trend downward over time. and a student for whom freshmen year was a struggle may expect future courses to be easier, and hence her GPA to trend upward. Without accounting for these anticipated trends, a positive information shock may erroneously be inferred as a negative one or visa-a-versa. Therefore, what is needed is a measure of GPA relative to this anticipated trend. More specifically, one needs to know the respondents' prior probability distributions (i.e., their belief in the Fall 2006 survey) about their GPA at the start of Fall 2007.[17] In the absence of this information, one may conclude positive information for negative information when the individual's GPA in Fall 2007 decreases by less than the individual had anticipated. To highlight this point, consider the following example: Individual A's GPA is up by 0.3 point at the beginning of Fall 2007 (relative to Fall 2006 GPA), while that of individual B is down by 0.1 point. Further assume

[17]To be more precise, the change in GPA between the two surveys actually is the difference in cumulative GPA at the beginning of Fall 2007 (which would be the cumulative GPA realized at the end of Spring 2007) and the cumulative GPA at the beginning of the quarter when the individual took the initial survey. Therefore, Fall 2007 GPA actually means the GPA realized at the end of Spring 2007. The academic year consists of the Fall, Winter, and Spring quarters (in that order).

that, when taking the initial survey in Fall 2006, individual A had forecast her GPA at the beginning of Fall 2007 to be up by 0.4 points, while individual B expected his to be down by 0.2 point.[18] In the absence of information on the individuals' beliefs, the researcher would deduce that individual A experienced a positive change and that individual B experienced a negative change, when in fact the converse is true.

In order to understand the responsiveness of beliefs about future GPA, it is important to discern the information content of the realized Fall 2007 GPA. ε_{it+1} in equation (1) can be expressed as a function of new information:

$$\varepsilon_{it+1} = h[\omega_{it+1} - E(\omega_{it+1}|\Omega_{it})].$$

Equation (1) can now be written as:

$$\Pr(X = 1|\Omega_{it+1}) - \Pr(X = 1|\Omega_{it}) = h[\omega_{it+1} - E(\omega_{it+1}|\Omega_{it})], \tag{2}$$

which basically states that the change in an individual's expectation between time t and $t+1$ about some event **X** that is realized at some point in the future is a function of surprises between time t and $t+1$. This equation highlights the challenges in studying the updating of expectations; not only does the researcher need data on expectations of an agent over time, but also needs to identify new information between periods. Bernheim (1988) uses assumptions on prior expectations in order to identify a model of revisions of Social Security benefit expectations. However, this approach defeats the purpose of collecting subjective expectations data. Dominitz (1998) faces the same problem in his analysis of revisions of earnings expectations in the SEE and, in the absence of knowledge about what the new information is, cannot pin down the causal explanation for the revision in expectations.

To come up with a metric of new information that wasn't anticipated at time t, I use information on the individual's cumulative GPA at the end of Spring 2007 (which is not known at time t but has been realized at time $t+1$; see Figure 1). I define ω_{it+1} to equal 1 if i's cumulative GPA at the end of Spring 2007 was at least as much as her cumulative Fall 2006 GPA, i.e.:

$$\omega_{it+1} = \begin{cases} 1 \text{ if Spring 2007 GPA}_i \ \geq \ \text{Fall 2006 GPA}_i \\ 0 \text{ otherwise.} \end{cases}$$

[18] Note that these forecasts are in Ω_t, the individuals' information sets at time t. Thus, any expectations about future events reported at time t are conditional on these forecasts.

$E(\omega_{it+1}|\Omega_{it})$ is i's belief elicited at time t (in the Fall 2006 survey) that $\Pr(\omega_{it+1} = 1|\Omega_{it})$. More specifically, in the initial survey, students were asked about the percent chance (probability) that their GPA at the end of Spring 2007 would be at least as much as their Fall 2006 GPA. Figure A1 in the Appendix shows the distribution of this belief. To construct the metric, the belief was normalized to zero-to-one scale.

Therefore, the metric $\omega_{it+1} - E(\omega_{it+1}|\Omega_{it})$ varies from -1 (this is the case of extreme negative surprise where the individual expected the Spring 2007 GPA to be above the threshold with certainty in the Fall 2006 survey but that did not happen) to 1 (in the case of extreme positive surprise). The histogram in Figure 3 depicts the distribution of the metric in the sample. The metric varies between -1 (extreme negative surprise) to 0.8 in the sample. The mean value of the metric is -0.23, which suggests that individuals tend to be overoptimistic about their future academic performance.[19] The metric is significantly positively correlated with realized GPA changes (a Spearman rank correlation of 0.57 at the 0.01% level).

Panel A of Figure 3 depicts the local linear estimates of Equation (2), i.e., the regression of change in the Spring 2008 GPA beliefs on the new information metric. Revisions of Spring 2008 GPA expectations seem to be positively related to the new information. Individuals who receive positive information revise upward their prediction of Spring 2008 GPA only if the information metric is greater than 0.50, while individuals who receive negative information revise their predictions downward only if the information content is less than -0.50. In the intermediate range, i.e., -0.50 to 0.50, students don't revise their beliefs (the confidence interval cannot reject zero change). Panel B of Figure 3 estimates the regression function of Equation (2) where the content of new information is defined as before, but $\mathbf{X}$ is now the cumulative GPA in one's major at the time of graduation. Panel B shows that all individuals revise downward their beliefs about cumulative graduating GPA, although those doing better than expected in Spring 2007 revise them down by less. Relative to revisions in Spring 2008 GPA beliefs, individuals revise to a lesser degree their beliefs about their graduating GPA. There could be at least two reasons for this. First, the belief in question here is about the graduating GPA being above 3.5 (instead of an individual-specific threshold, as is the case for the Spring 2008 GPA). For

[19] Though recent studies have found that men tend to be more overconfident about their ability than are women (Niederle and Vesterlund, 2007), that is not the case here: The mean value of the metric is -0.215 for males (with a standard deviation of 0.48) and -0.239 for females (with a standard deviation of 0.53). This suggests that, on average, women in my sample tend to be more overconfident. However, I fail to reject the null that the two means are equal. Similarly, I don't find significant differences in the mean value of the metric for the different ethnic groups.

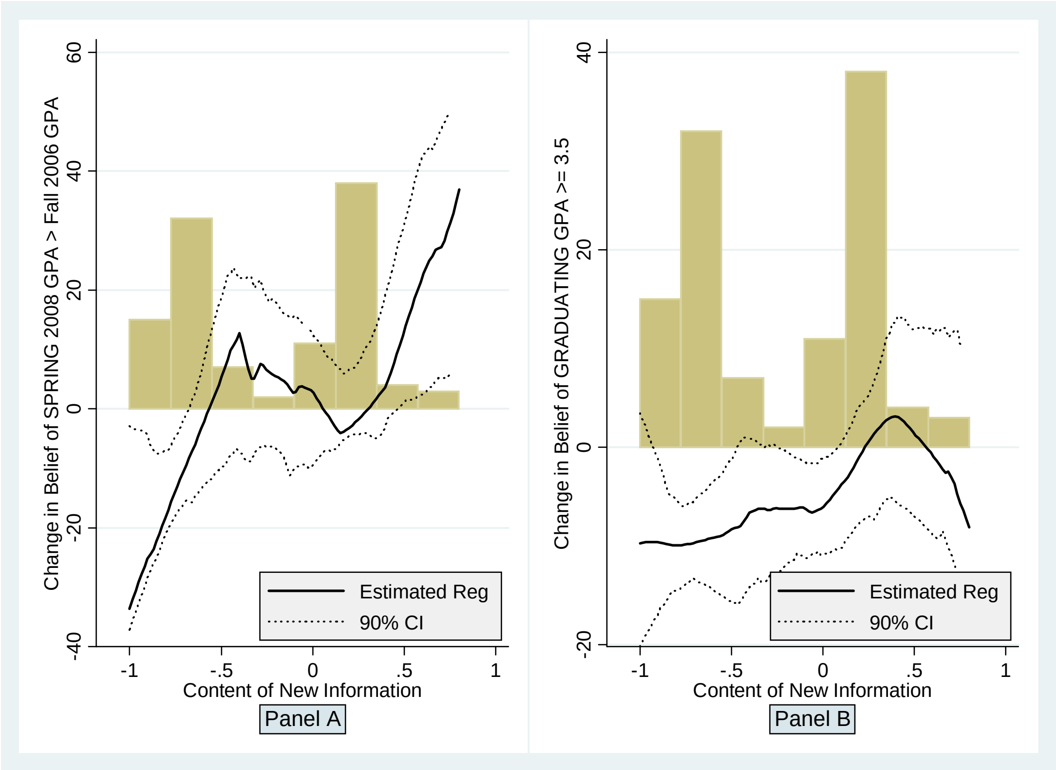

Figure 3: Local linear regressions of the change in Spring 2008 beliefs (Panel A) and Graduation GPA beliefs (Panel B) on *new* information revealed between the surveys. Confidence intervals estimated from 200 bootstrap sampling distributions.

individuals with very high or low GPAs, a threshold of 3.5 will not be binding, and therefore any new information should not cause them to revise their beliefs much. Second, since individuals have another year and a half of classes to take before the cumulative graduating GPA outcome is realized (and all these classes will be counted toward the graduating GPA), the mechanical effect of any new information contained in the Spring 2007 GPA should be lower, especially if students believe that Spring 2007 GPA gives them little information about their long-term performance.

Table 5 reports the OLS estimates of regressing the change in Spring 2008 GPA beliefs on realized GPA change and the information metric in columns (1)-(3) as well as the corresponding estimates for the change in Graduation GPA beliefs in columns (7)-(9). As in Figures 2 and 3, revisions in Spring 2008 GPA beliefs and Graduation GPA beliefs are positively related to both realized changes in GPA and the information metric. However, in an equation with both the realized GPA change and the information metric (columns 3 and 9), only the latter is significant (at the 10% level) for revisions in Spring 2008 GPA beliefs. I interpret this to mean that the information metric has an expectational element not captured in the GPA change.

Though GPA is a noisy signal of one's ability, it is also a function of one's field of study. The estimates shown in Table 5 as well as in Figures 2 and 3 would be biased if I don't account for the fact that individuals could switch majors in response to new information.[20] In the sample, 14 of the 117 respondents (~12%) switch majors between the two surveys.[21] Columns (4)-(6) and (10)-(12) in Table 5 report the OLS estimates for the sample excluding respondents who switched majors between the two surveys. Though qualitatively similar to those for the full sample, the estimates are somewhat larger in magnitude. This finding suggests that there is indeed some strategic switching of majors on the part of respondents, i.e., students who receive negative information may be switching to easier majors or those who receive positive information may decide to pursue harder majors. Closer examination of students who drop majors shows that the mean value of the metric for them is lower (-0.261 versus -0.224 for students who don't switch majors; difference is not statistically significant), suggesting that negative information is associated with switching majors (Arcidiacono, 2004, also finds that poor performance is correlated with switching majors). This issue is explored in more detail in Section 5. Figure A2 in the Appendix estimates Equation (2) by excluding those respondents. The overall pattern is similar to that in Figure 3.

The analysis in this section is robust to altering the metric and defining ω_{it+1} to equal 1 if the Spring 2007 GPA is within 0.1 points of Fall 2006 GPA. Finally, it should be pointed out that I include only the Spring 2007 GPA in ω_{it+1}. It is plausible that individuals are using some other sources of information in updating their beliefs of future academic performance. However, as mentioned earlier, it is nearly impossible to identify all the new information. The analysis in this section shows that, to address the question of how individuals update their beliefs, not only is high-frequency data needed, but the researcher also needs to observe innovations in the individual's information set. Nonetheless, it is certainly reassuring that, despite using a metric that contains information only about the Spring 2007 GPA, students are found to revise their beliefs in somewhat rational ways.

[20] Another possibility is that students may take easier (harder) elective courses upon receipt of negative (positive) information about their ability. Unfortunately, I cannot address this issue with my data (one would need to observe the courses that a student intended to take in the future as well as the courses the student actually ended up taking, and some measure of the difficulty of the courses). Estimates would most likely be biased downward if this possibility is not considered.

[21] Here, switching a major means that, at the time of the follow-up survey, an individual was pursuing a major different from the one at the time of the first survey and that the individual had also taken at least one course in the new major.

3.2 Revisions of various major-specific beliefs

The discussion in Section 3.1 highlights the breadth of data required to understand the revision of expectations in response to new information. Unfortunately, I don't have data for similar metrics of surprise for other determinants. This section investigates how individuals revise their beliefs for other major-specific outcomes in response to new information revealed about academic ability. Beliefs about certain outcomes, such as graduating in 4 years, may change in response to this information. On the other hand, beliefs about outcomes, such as reconciling work and family, may not change in response to this information. For beliefs for other outcomes, such as parents' approval, it's less clear: If students believe that parents' approval is linked with how well they do in a major, then those beliefs may change in response to new information about ability.

This section also analyzes how students revise their beliefs for the various outcomes associated with majors other than their current major. It's not clear how beliefs for various outcomes in different majors should change in response to new information acquired about ability in a specific major. If learning is entirely major-specific, then information about ability in one's own major should not lead to meaningful revisions in beliefs for outcomes in other majors. However, if learning also has a general dimension, then beliefs for outcomes in other majors should be revised in a manner similar to corresponding revisions for own major.

Figure 4 depicts the local linear polynomial estimates of the regression of change in beliefs in the three different major categories for 1) graduating in 4 years, 2) graduating with a GPA$\geq$3.5, 3) expected hours per week spent on coursework, and 4) approval of parents on the new information acquired between the two surveys. Second preferred major and second pursued major are pooled together as second major in the figure, while revisions of beliefs for dropped major are not reported because of few observations.

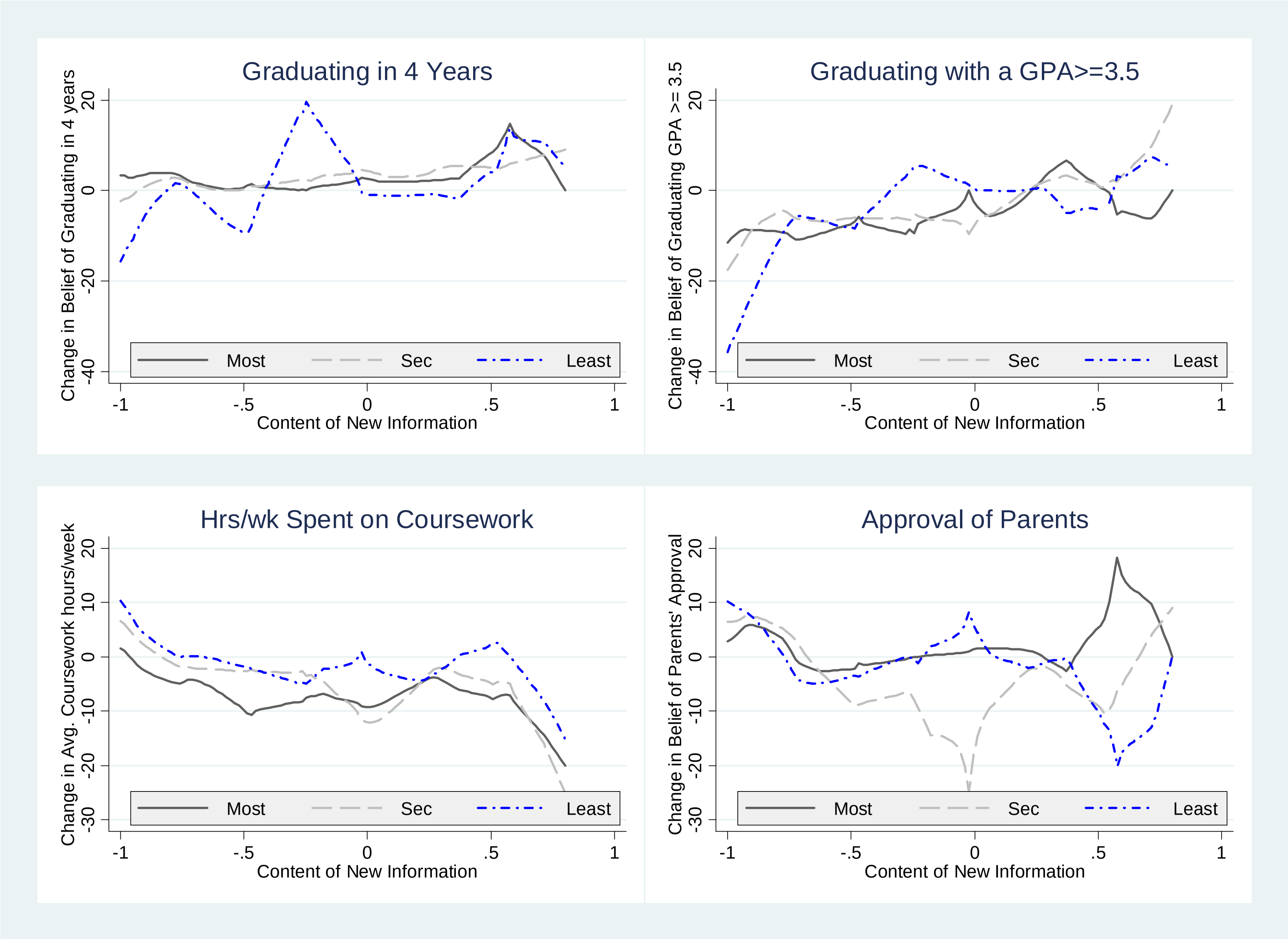

Figure 4: Local linear regressions of the change in beliefs for 1) graduating in 4 years, 2) graduating with a GPA$\geq$3.5, 3) expected hours per week spent on coursework, and 4) approval of parents (in one's *most* preferred/current major, *second* (most preferred) major, and *least* preferred major) on *new* information about ability revealed between the surveys. Standard errors on these regressions are not reported.

The top-left panel in Figure 4 shows that, for graduating in 4 years, students revise their beliefs only for extreme changes in the information content, and the same relationship is observed for all three major categories. More specifically, students revise downward (upward) their beliefs about graduating in 4 years on receipt of very negative (positive) information. A similar pattern is observed in the case of revised beliefs of graduating with a GPA of ≥ 3.5 (top-right panel of Figure 4). Conversely, as depicted in the bottom-left panel of Figure 4, a negative relationship is observed between revisions of beliefs about coursework hours per week and the information metric. Students who receive positive (negative) information about their academic ability revise their beliefs downward (upward) about expected hours per week spent on coursework in all three major categories.[22] This result is consistent with Stinebrickner and Stinebrickner (2007), who find a causal effect of studying on academic performance. On the other hand, revisions of beliefs for outcomes such as approval of parents (bottom-right panel of Figure 4) don't seem to vary in any particular way with the new information. Revisions of beliefs for other outcomes are reported in Figure A3; there is no systematic pattern in the revision of these beliefs either.

On the whole, these figures suggest that, at least for some outcomes, there is a clear and logical pattern in which beliefs are revised. Moreover, similar patterns in revisions in beliefs for graduating in 4 years, graduating with a GPA of at least 3.5, and expected coursework hours per week for the different major categories are in line with results above that learning is not entirely major specific, and that information about ability in one's own major leads students to revise their beliefs for outcomes not only in their own major but also in other majors.

4 Are Students Bayesian?

Before a formal characterization of the belief-updating process, I present suggestive evidence that the learning process is consistent with a Bayesian learning approach. I define a dummy, U_i, that equals 1 if, in the initial survey, the individual was *more* uncertain about the occurrence

[22] This pattern between beliefs about coursework hours/week and new information about ability would be obtained if (perceived) ability affects the marginal utility of effort negatively, i.e., students with higher perceived ability spend fewer hours/week on coursework to attain the same GPA. In that case, students who receive a positive signal about ability should decrease the number of hours per week that they expect to spend on coursework.

of the major-specific outcome, and zero otherwise. More specifically:

$$U_i = \begin{cases} 1 \text{ if } 25 \leq \Pr(X = 1|\Omega_{it}) \leq 75 \\ 0 \text{ otherwise.} \end{cases}$$

The top panel of Table 6 regresses $|\Pr(X = 1|\Omega_{it+1}) - \Pr(X = 1|\Omega_{it})|$, the absolute change in beliefs between the two surveys for each of the binary outcomes, on the dummy U_i and a constant term.[23] The coefficient on U_i is positive and statistically significant for each of the major-specific outcomes, suggesting that individuals who are more uncertain about the major-specific outcomes in the initial survey make greater absolute revisions in their beliefs. Since responses in the tail can only be updated in one direction and the finding that respondents in the middle of the belief distribution update the most may be driven by that, the bottom two panels of Table 6 report the results of the same regression on the sample with non-negative and non-positive revisions, respectively. As before the results are consistent with a Bayesian learning approach: Individuals with more uncertainty update the most.

I next formalize the nature of the belief-updating process for the binary outcomes. The assumption is that individuals adopt a Bayesian learning approach, and that beliefs of the individuals can be characterized by a beta distribution (which is ideally suited to analyze binary events). Then the posterior probability P_{ijm}^{t+1} (individual i's probabilistic belief of outcome j happening in the case of major m) is given by (see Viscusi and O'Connor, 1984; and Viscusi, 1997):

$$P_{ijm}^{t+1} = \frac{\alpha}{\alpha + \beta} P_{ijm}^{t} + \frac{\beta}{\alpha + \beta} I_{ijm}, \tag{3}$$

where P_{ijm}^{t} is i's prior belief of outcome j in major m, I_{ijm} is new information that i acquires about this outcome between period t and $t + 1$, α is the precision of the prior, and β is the precision of the new information. In this framework, the new information is equivalent to observing additional Bernoulli trials about the occurrence of the various major-specific outcomes. In the context of this study, the prior belief refers to the subjective belief elicited in the initial survey, while the posterior refers to the belief elicited in the follow-up survey. To empirically estimate Equation (3), the researcher needs to determine the individual's information set at both times t and $t + 1$, which is almost impossible (Cunha et al., 2004).

In order to estimate Equation (3), I use the information metric introduced in Section 3.1

[23] Here, I interpret responses in the range of 25-75 (on a scale of 0-100) as exhibiting more uncertainty. Results are robust to alternate definitions as well.

(the metric that captures the extent of new information that an individual acquires about her academic ability in her current major) as a proxy for the new information. Needless to say, the information metric only partially identifies the new information that individuals receive between the two surveys. Moreover, information about academic ability in one's current major may or may not affect one's beliefs about outcomes associated with other majors or beliefs for outcomes other than academic achievement in the same major. I use the following regression framework for the empirical investigation of (3):

$$P_{ijm}^{t+1} = \gamma P_{ijm}^{t} + \eta I_{ijm} + D_{im} + \varepsilon_{ijm}, \tag{4}$$

where D_{im} is a dummy that equals 1 for major m and zero otherwise, ε_{jm} is a random error term, and:

$$\gamma = \frac{\alpha}{\alpha+\beta}; \quad \eta = \frac{\beta}{\alpha+\beta}.$$

The empirical specification includes a major dummy (D_{im}) to allow for common shocks within a major.[24] In this framework, the coefficients γ and η show the nature of the learning process. One would expect γ to be equal to 1 and η to be equal to 0 if the individual depends solely on her prior information and does not learn any new information about the outcome from the information metric. On the other hand, if the new information is really valuable, γ would be close to zero and η would be large. Equation (4) is estimated for each of the binary major-specific outcomes and for three different majors in the individual's choice set.[25] The results are shown in Table 7. The estimates are between the two extremes, and the prior belief continues to play a significant role in almost all the cases. However, γ is smaller than 1 in most cases, suggesting that the posterior beliefs do not solely depend on the prior belief. The table shows that η is small in magnitude but statistically significant in more than half the cases. These results are broadly consistent with a Bayesian learning model.

Another object of interest is the importance of new information relative to the prior, which is denoted as R and given as:

$$R = \frac{\beta}{\alpha} = \frac{1}{\gamma} - 1.$$

Higher values of R would imply greater relative informativeness of the new information.

[24] Regressions that were run excluding major-specific shocks (D_{im}) yield similar results qualitatively, and are available upon request from the author.

[25] The above-mentioned interpretation of the model does not apply to the continuous outcomes (coursework hours per week; job hours per week; expected salary); I discuss the updating of expected salary in detail in Section 6.

Table 8 shows the estimates of R. In most cases, R is less than 1, suggesting that this new information is not very valuable. For outcomes such as approval of parents, new information seems to be less relatively valuable ($|R| < 0.35$). This finding is plausible because one would expect students to be aware of their parents' perceptions of different majors when they start college, and therefore they should be less likely to receive any valuable information about parents' approval over time. Similarly, priors for outcomes such as graduating in 4 years and graduating with a GPA of at least 3.5 receive a larger relative weight in the updating process. On the other hand, the metric R is larger for outcomes related to the workplace such as finding a job or enjoying working at the jobs. This suggests that the new information is relatively more valuable for workplace outcomes.

The table also reveals interesting patterns of belief-updating across the other major categories. The estimates of R for the second major are statistically similar to those for the current major, indicating a similar process of belief-updating in both major categories. However, relative to estimates for the current major, estimates are statistically different for the dropped major and second preferred major categories. The estimate of R is larger for most outcomes for dropped majors suggesting a larger relative importance of the new information for belief-updating in that category. On the other hand, the estimates are substantially smaller for the second preferred major indicating lower relative importance of information (about ability in one's current major) in updating beliefs for outcomes in that category. In the case of the least preferred major, the picture is unclear: for some outcomes, the estimates of R are comparable to those for the current major, while for others, the estimates are smaller. Since the information metric is basically a measure derived from how students learn about unobserved ability by taking courses in pursued fields, it should not be surprising that the information metric is relatively more informative in explaining revisions in beliefs for majors that an individual has pursued (current major, dropped major, second major) than in explaining revisions in beliefs for non-pursued majors (least preferred major and second preferred major).

5 Experimenting with Majors

Students may be uncertain about their ability and other outcomes when choosing a major. In fact, the analysis in sections 3 and 4 shows that students revise their beliefs in meaningful ways in response to information. Over time, when new information arrives, they may choose to drop out of college or switch to a different major that they deem to be a better fit (Manski, 1989; Altonji, 1993; Arcidiacono, 2004; Malamud, 2007; Stinebrickner and Stinebrickner, 2008). In the context of the current setting, Northwestern University, dropouts are not very common. Completion rates for the 2006 and 2007 undergraduate class were 93%. Instead, students are more likely to switch majors during the course of their undergraduate studies. Of the 117 survey respondents, 14 (~12%) switched their majors between the two surveys.

I first outline a simple model of college major choice. At time t, individual i derives utility $U_{ikt}(\mathbf{a}, \mathbf{c}, X_{it})$ from choosing major k. Utility is a function of a vector of outcomes $\mathbf{a}$ that are realized in college, a vector of outcomes $\mathbf{c}$ that are realized after graduating from college, and individual characteristics X_{it} (outcomes in vectors $\mathbf{a}$ and $\mathbf{c}$ are described in Section 2). Since the outcomes in vectors $\mathbf{a}$ and $\mathbf{c}$ are uncertain at time t, i possesses subjective beliefs $P_{ikt}(\mathbf{a}, \mathbf{c})$ about the outcomes associated with choice of major k for all $k \in C_i$. Individual i chooses major m at time t if

$$m = \arg\max_{k \in C_i} \int U_{ikt}(\mathbf{a}, \mathbf{c}, X_{it}) dP_{ikt}(\mathbf{a}, \mathbf{c}). \tag{5}$$

However, over time, new information may arrive that may lead the individual to update her beliefs about any of the major-specific outcomes. A change in an individual's beliefs about her ability (graduating GPA or probability of completing the major in 4 years), match quality in college (outcomes like enjoying coursework), or match quality in workplace (enjoying working at the jobs or expected earnings at the jobs) may lead the individual to switch to a major that yields higher expected utility.[26] To understand the pattern of switches in major, one would need not only data on the subjective beliefs about major-specific outcomes at several points in time, but also data on how the respondent *believes* the subjective beliefs will evolve over time. For example, as outlined in Section 3.1, one cannot simply infer positive news from observing a GPA increase from one quarter to the next. Instead, one needs to observe how much the student anticipated that her GPA would change over that time horizon. Having very little data on the prior distributions of the respondents' beliefs, I can only conduct a descriptive analysis of why individuals experiment with different majors. Moreover, I focus my analysis primarily on the role of learning about ability in the decision to switch majors.

Individuals who switch majors experience a small average gain of about 0.17 point in their GPA.[27] Fewer than 50% of these individuals experience a positive change in their GPA, sug-

[26] Here, as in Becker and Stigler (1977), I assume that preferences are stationary.

[27] This number comes from directly asking the respondents to report their major-specific GPA for the new major and

gesting that academic performance is not the only dimension that influences one's choice of major. Respondents were asked to assign weights to different reasons for dropping the major so that they summed to a 100. Table A2 in the Appendix reports the average weight assigned to each reason. Losing interest in the original major, getting interested in something else, and finding the initial major too challenging stand out as the main reasons for dropping the initial major.

The probability of switching majors is related to realized changes in GPA and the information metric in a meaningful way: A unit increase in the information metric is associated with a decrease of about 1.5% in the probability of switching majors (which is 11.96% in the sample), while a unit increase in GPA (between Winter 2007 and the beginning of Fall 2006) is associated with a decrease of about 1% in the probability of switching majors.[28] Revisiting Table 3, which regresses the change in beliefs for each outcome onto dummies for the different major categories, shows that revisions in beliefs for outcomes in the dropped major are statistically similar to those for the current major, except for graduating in 4 years.[29] Relative to one's current major, students revise down their beliefs for graduating in 4 years for the dropped major by an additional 8.5 points. Though none of the other changes is significant (presumably because of small sample sizes), changes in beliefs about enjoying coursework and expected salary at the age of 30 seem to be quantitatively different from the corresponding changes in one's current major. If one were to assume that these changes accurately reflect the changes in beliefs at the instant when an individual switched her major, it seems that negative changes in beliefs about graduating in 4 years, enjoying coursework, and expected salary at age 30 are associated with the dropping of a major.[30]

A switch in majors may arise because of either downward (upward) revisions in beliefs for some positive (negative) outcomes in own original major, or upward (downward) revisions in some positive (negative) beliefs for in other majors, or both. The analysis so far does not inform us about the extent to which major switchers are responding to information for their

then comparing it to their GPA in the previous major.

[28]These estimates are, however, not statistically significant.

[29]The table reports the change in beliefs *after* the individual has already switched her major. If we really want to understand what led an individual to switch her major, we would need to observe her beliefs right before she made the decision, which I don't have. Nonetheless, it is useful to go through this exercise to see how beliefs changed between the surveys for the dropped major category versus other categories.

[30]It could be that once an individual has decided to drop a major, she devalues the outcomes associated with that major in order to rationalize her choice (cognitive dissonance; see Festinger, 1957). However, estimates in Table 3 indicate that this is not the case. For example, beliefs about enjoying coursework and enjoying work at the jobs are revised downward in all major categories, not only for the dropped major.

own major as opposed to information about a different major. Table 9 shows the weighted mean difference in initial beliefs for each outcome for the dropped majors for individuals who dropped the major and those who never dropped the major. More precisely, the metric shown in the first column of the table is $\frac{1}{7}\sum_{m=1}^{7}(\overline{b_{jm}^{D_m}} - \overline{b_{jm}^{(1-D_m)}})$, where $\overline{b_{jm}^{D_m}}$ $(\overline{b_{jm}^{(1-D_m)}})$ is the mean belief for outcome j in major m reported by respondents who dropped (never dropped) major m, and the number of major categories considered is 7. Column 2 of the table reports the mean deviation (between individuals who dropped the major and those who never dropped the major) in beliefs for outcomes in other majors, i.e., $\frac{1}{7}\sum_{m=1}^{7}(\overline{b_{jm}^{D_k}} - \overline{b_{jm}^{(1-D_k)}})\ \forall\ k \neq m$, where $\overline{b_{jm}^{D_k}}$ $(\overline{b_{jm}^{(1-D_k)}})$ is the mean belief for outcome j in major m reported by respondents who dropped (never dropped) major k, and $k \neq m$. The first column shows that students who dropped the major had more optimistic (higher) initial beliefs for outcomes in the dropped major relative to individuals who never dropped the major. Moreover, it is not the case that these students had more optimistic beliefs about all majors: For other majors, the deviation in mean beliefs is much smaller and close to zero for half of the outcomes, as can be seen in column 2. In particular, the optimism reflected in initial beliefs for outcomes realized in college (graduating in 4 years, graduating with a GPA of at least 3.5, enjoying coursework), finding a job, and expected salary for majors that are eventually dropped is much higher when compared to the deviations in non-dropped majors. This suggests that, over time students who switch majors are primarily responding to information in their own major.

6 Evolution of Salary Expectations

Large earnings premiums exist across majors (Daymont and Andrisani, 1984; Garman and Loury, 1995). This section focuses on whether, over time, students have more accurate expectations of earnings conditional on major. Although, in both surveys, students reported expected income at the age of 30 for various majors, no objective measures exist to which their responses can be compared. This is because Northwestern University does not follow its alumni. Moreover, even if such data existed, for various reasons—from variation in information sets to selection into occupations, to time nonstationarity in labor markets—the historical statistics typically cited as objective realities need not be such from the forward-looking perspective of the student. Therefore, instead I use students' responses to questions that asked for their prediction of the average annual starting salaries of Northwestern bachelor's degree graduates of the year in which they were surveyed. Responses to these question can be compared directly to actual salary realizations of Northwestern graduates, available from the Northwestern University Career Services. In the initial survey, students were asked: "*What do you think was the average annual starting salary of Northwestern graduates (of 2006) with Bachelor's Degrees in Category X?*". In the follow-up survey, the question asked was: "*What do you think was the average annual starting salary of Northwestern G graduates (of 2007) with Bachelor's Degrees in X?*" where $G = \{\text{Male, Female}\}$.

For the analysis, I assume that student i reports, $\overline{s_{im}^{2006}}$, the average gender-neutral salary for 2006 graduates in major m in response to the question asked in the initial survey. For the follow-up survey, the respondent also reported her subjective belief of fraction of females enrolled in major m, frac_{im}^{f}. To make the responses comparable across the two surveys, I compute $\overline{s_{im}^{2007}}$, the subjective gender-neutral average starting salary for 2007 graduates[31]. As in Betts (1996), I use the following metric to model the respondents' errors:

$$\ln\left|\frac{\overline{s_{im}^{Y}} - s_{obs\_m}^{Y}}{s_{obs\_m}^{Y}} * 100\right|, \tag{6}$$

where $\overline{s_{im}^{Y}}$ is respondent i's reported average starting salary in major m, and $s_{obs\_m}^{Y}$ is the true average salary for Northwestern graduates of in major m, in year Y. The top panel in Figure 5 shows the density of the metric in the two surveys. The distribution is shifted left in the Fall 2007 survey. This is consistent with students' predictions becoming more accurate over time.[32] The lower panel of the figure shows the density of the errors (i.e., the metric as in equation (6) but without the absolute value and the natural logarithm). The plot shows that both positive and negative errors get smaller over time.

For each respondent, in both surveys, there are three values of the metric: one for her current major, one for her second (preferred) major, and one for her least preferred or dropped major. Figure 5 pools them together. To understand whether there are systematic differences in how prediction errors change over time across the different major categories, columns (1) and (4) of Table 11 regress the absolute error on a constant term, and dummies for the different major

[31] This is simply: $(\text{frac}_{im}^{f} * \overline{s_{im}^{2007f}}) + (1 - frac_{im}^{f}) * \overline{s_{im}^{2007m}}$, where $\overline{s_{im}^{2007G}}$ is the respondent's prediction of the average starting salary of 2007 Northwestern graduates of gender G ($G = \{m, f\}$) in major m.

[32] This would be also consistent with the possibility that it was easier to predict labor market returns in 2007 relative to 2006. This is highly unlikely since the labor market conditions were similar over the period 2006-2007. Hence, I discount this possibility.

Responses may also change between the two surveys solely due to the fact that the questions were asked in different ways in the two instruments. This cannot be ruled out.

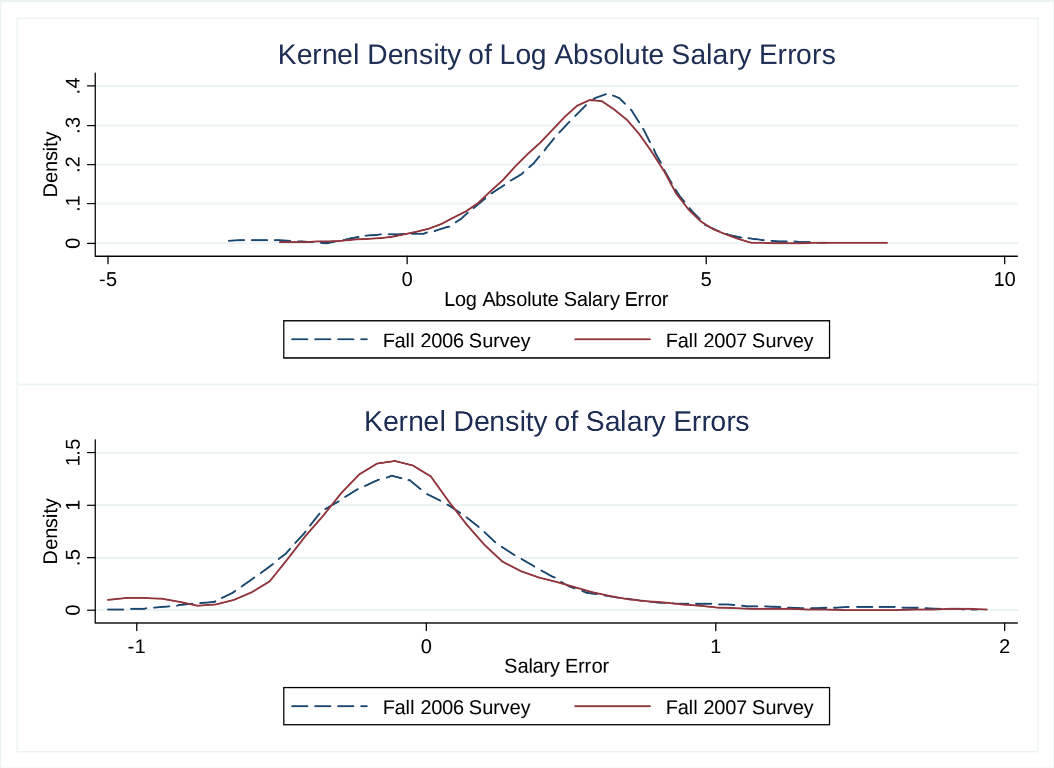

Figure 5: Distribution of starting salary errors in the two surveys.

categories for the 2006 and 2007 survey responses, respectively. The coefficient on the constant term, which indicates the error for current major, gets smaller over time (though the difference is not statistically different from zero). Results of two F-tests are also reported in each column. Since an individual may have better information about returns to her most preferred major, the purpose of the first F-test is to determine whether errors in majors excluding the current major are different from those in current major. Similarly individuals may invest less in informing themselves about returns to majors that they have never seriously considered and may make larger errors when reporting salaries for such majors. The second test precisely checks for this by testing if the coefficients on the least preferred major and second preferred major (majors that an individual never pursued in the past) are statistically different from zero. Column (1) shows that the null of no statistically significant differences cannot be rejected for either test for responses in the initial survey, suggesting that errors are similar across the various majors. However, column (4) shows that the null is rejected for both tests for the follow-up survey. The estimates indicate that errors are significantly larger for the dropped major and least preferred major category. It should be pointed out that the mean size of the error for, say, the least preferred major in the initial survey and follow-up survey is similar (it is 2.86+0.21 in the initial survey, versus 2.68+0.32 in the follow-up survey). While, over time, students are making smaller errors in their most preferred major, their errors remain unchanged for non-pursued majors.

To get a sense of whether students are more likely to overpredict or underpredict earnings when making errors in majors other than the pursued major, columns (2) and (3) report the estimates of the same regression as in column (1) with the error in the initial survey as the dependent variable but restricts the sample to respondents who overpredict and underpredict, respectively. Corresponding estimates with errors in the follow-up survey as the dependent variable are reported in columns (5) and (6) of the table. The results indicate that individuals are more likely to underpredict earnings for the least preferred major.

Columns (7)-(9) of Table 11 run the same regression with the error in the follow-up survey as the dependent variable, except that the error in the initial survey is now also included as an explanatory variable. Though the coefficients on the initial error term are positive, suggestive of persistence in errors, none of them are statistically different from zero. Inclusion of the initial errors does not qualitatively change the regression estimates.

The results in this section provide suggestive evidence that students tend to make similar errors in predictions of starting salaries in their pursued majors, but underpredict earnings in their least preferred major. There is weak evidence that the predictions become more accurate over time for pursued majors, but remain unchanged for non-pursued majors.

7 Conclusion

Students use their preferences and beliefs about future outcomes when making their schooling choices under uncertainty. A standard approach to infer preferences from schooling choice data has been to impose assumptions on expectations. Due to various shortcomings of this approach, Zafar (2009) elicits subjective data on counterfactual majors from Northwestern University undergraduates and incorporates the data into a choice model of college majors. Kaufmann (2009) and Arcidiacono et al. (2010) adopt a similar approach and integrate counterfactual subjective beliefs data in models of college attendance and college majors, respectively. This method does not require an understanding of how students form expectations. However, understanding of expectations formation is required for an informed analysis of schooling decisions, and for credible prediction. Unfortunately, little is known about how individuals form expectations (Manski, 2004). This paper enhances our limited understanding of how students form expectations by focusing on how college students revise expectations for outcomes associated with choice of college major.

In the paper, revisions of expectations of future GPA are found to be positively related to changes in GPA between the two surveys. However, unlike in existing studies, I collect data that directly identify some new information that students acquire between the two surveys, which allows me to pin down some of the causal mechanisms that lead individuals to revise their beliefs. By combining elicited expectations of GPA at various points in time with their realizations, I form an information metric about academic ability and find that individuals update their beliefs for various major-specific outcomes in response to this information metric in appropriate ways. For example, individuals who receive positive information about their academic performance revise down their beliefs about number of hours per week that they expect to spend on coursework, and revise their beliefs upward if the information is very negative. Section 4 shows that modifications in expectations about various major-specific outcomes are consistent with a Bayesian learning framework: Both prior beliefs and new information are significant in the updating process. I also find that individuals who are more uncertain about the major-specific outcomes in the initial survey make greater absolute revisions in their beliefs. Learning, in particular about beliefs in original major, seems to play a role in the switching of majors.

The novel panel data on beliefs about outcomes in counterfactual majors allows me shed light on whether learning is major-specific or general. While a well-developed literature on this question exists with regards to learning in the labor market, little is known about learning in the context of schooling. This is because few studies collect data on beliefs about counterfactual choices and, to my knowledge, none collect a panel of such beliefs. Section 3 presents suggestive evidence that learning is not entirely major-specific, and that it also has a general component. Patterns of belief updating and resolution of uncertainty for the different binary outcomes is similar across the different major categories. Beliefs for binary outcomes in non-pursued majors respond in a manner similar to corresponding beliefs in own major in response to new information. However, the new information is relatively less useful in the updating process for beliefs in non-pursued majors. What we can learn from this paper about the updating of continuous outcomes (such as earnings) is limited, because I do not have data on the underlying distribution for the continuous outcomes. Section 6 analyzes how errors in students' predictions of salaries of recent graduates evolve between the two surveys. I find that prediction errors in starting salaries for pursued majors get smaller over time, but stay unchanged for non-pursued majors.

At least two directions can be taken from here. The first deals with the methodological aspect of this paper. As mentioned in Sections 3 and 4, identifying the information set of an individual is an extremely daunting task. This paper focuses only on innovations in information about academic ability since that is the only part of the information set I can identify. To enhance our understanding of expectations formation, it is crucial to collect repeated data on subjective expectations over a short time horizon and to identify changes in one's information set. However, as argued in Manski (2004), rich longitudinal data on subjective expectations may not suffice to help in understanding expectations formation, and probing students to learn how they perceive their environments may be informative.

From an applied aspect, it seems that students are forming their beliefs for various major-specific outcomes even before they come to college. For most outcomes, the prior belief continues to be important. In attempting to understand the choice of college majors, it might be useful to focus on students at earlier stages of their schooling (for example, in high school) and analyze their subjective beliefs.

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8 Appendix

8.1 Survey Excerpt

The following introduction was read and handed to the respondents at the start of the survey:

> *"In some of the survey questions, you will be asked about the PERCENT CHANCE of something happening. The percent chance must be a number between zero and 100. Numbers like 2 or 5% indicate "almost no chance," 19% or so may mean "not much chance," a 47 or 55% chance may be a "pretty even chance," 82% or so indicates a "very good chance," and a 95 or 98% mean "almost certain." The percent chance can also be thought of as the NUMBER OF CHANCES OUT OF 100.*

The following set of questions was asked for each of the relevant categories. The questions below were asked for Natural Sciences.

Q1 If you were majoring in Natural Sciences, what would be your most likely major?

Q2 If you were majoring in Natural Sciences, what do you think is the percent chance that you will successfully complete this major in 4 years (from the time that you started college)? (Successfully complete means to complete a bachelors)

NOTE: In answering these questions fully place yourself in the (possibly) hypothetical situation. For example, for this question, your answer should be the percent chance that you think you will successfully complete your major in Natural Sciences in 4 years IF you were (FORCED) to major in it.

Q3 If you were majoring in Natural Sciences, what do you think is the percent chance that you will graduate with a GPA of at least 3.5 (on a scale of 4)?

Q4 If you were majoring in Natural Sciences, what do you think is the percent chance that you will enjoy the coursework?

Q5 If you were majoring in Natural Sciences, how many hours per week on average do you think you will need to spend on the coursework?

Q6 If you were majoring in Natural Sciences, what do you think is the percent chance that your parents and other family members would approve of it?

Q7 If you were majoring in Natural Sciences, what do you think is the percent chance that you could find a job (that you would accept) immediately upon graduation?

Q8 If you obtained a bachelors in Natural Sciences, what do you think is the percent chance that you will go to graduate school in Natural Sciences some time in the future?

Q9 What do you think was the average annual starting salary of Northwestern MALE graduates (of 2007) with Bachelor's Degrees in Natural Sciences?

Q10 What do you think was the average annual starting salary of Northwestern FEMALE graduates (of 2007) with Bachelor's Degrees in Natural Sciences?

Now look ahead to when you will be 30 YEARS OLD. Think about the kinds of jobs that will be available for you and that you will accept if you successfully graduate in Natural Sciences.

NOTE that there are some jobs that you can get irrespective of what your Field of Study is. For example, one could be a janitor irrespective of their Field of Study. However, one could not get into Medical School (and hence become a doctor) if they were to major in Journalism.

Your answers SHOULD take into account whether you think you would get some kind of advanced degree after your bachelors if you majored in Natural Sciences.

Q10 What kind of jobs are you thinking of?

Q11 Look ahead to when you will be 30 YEARS OLD. If you majored in Natural Sciences, what do you think is the percent chance that you will enjoy working at the kinds of jobs that will be available to you?

Q12 Look ahead to when you will be 30 YEARS OLD. If you majored in Natural Sciences, what do you think is the percent chance that you will be able to reconcile work and your social life/ family at the kinds of jobs that will be available to you?

Q13 Look ahead to when you will be 30 YEARS OLD. If you majored in Natural Sciences, how many hours per week on average do you think you will need to spend working at the kinds of jobs that will be available to you?

When answering the next two questions, please ignore the effects of price inflation on earnings. That is, assume that one dollar today is worth the same as one dollar when you are 30 years old and when you are 40 years old.

Q14 Look ahead to when you will be 30 years old. Think about the kinds of jobs that will be available to you and that you will accept if you graduate in Natural Sciences. What is the average amount of money that you think you will earn per year by the time you are 30 YEARS OLD?

Q15 Now look ahead to when you will be 40 years old. Think about the kinds of jobs that will be available to you and that you will accept if you graduate in Natural Sciences. What is the average amount of money that you think you will earn per year by the time you are 40 YEARS OLD?

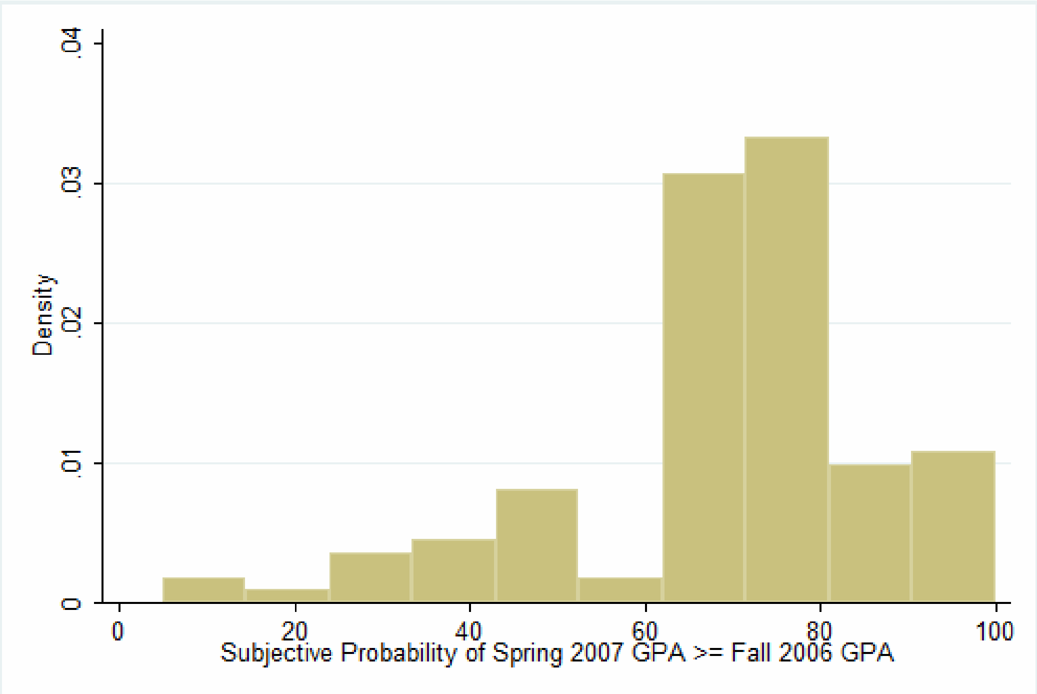

Figure A1: Distribution of the subjective belief of Spring 2007 GPA being at least as much as the Fall 2006 GPA (reported on a scale of 0-100).

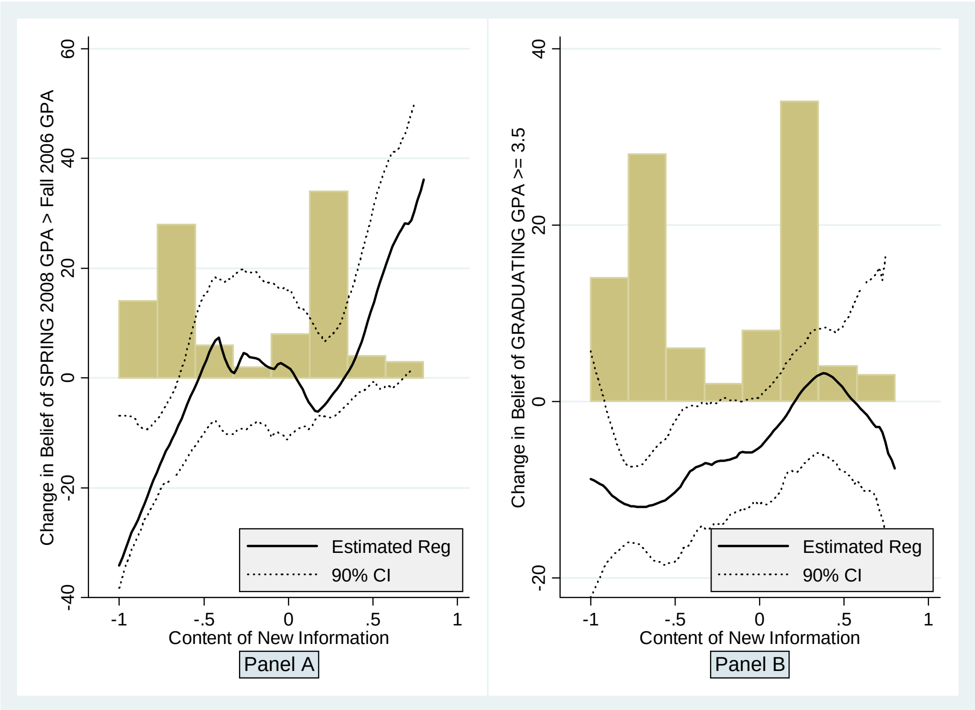

Figure A2: Local linear regressions of the change in Spring 2008 beliefs (Panel A) and Graduation GPA beliefs (Panel B) on *new* information revealed between the surveys. Confidence intervals estimated from 200 bootstrap sampling distributions. Sample only includes respondents who had the same major in the two surveys.

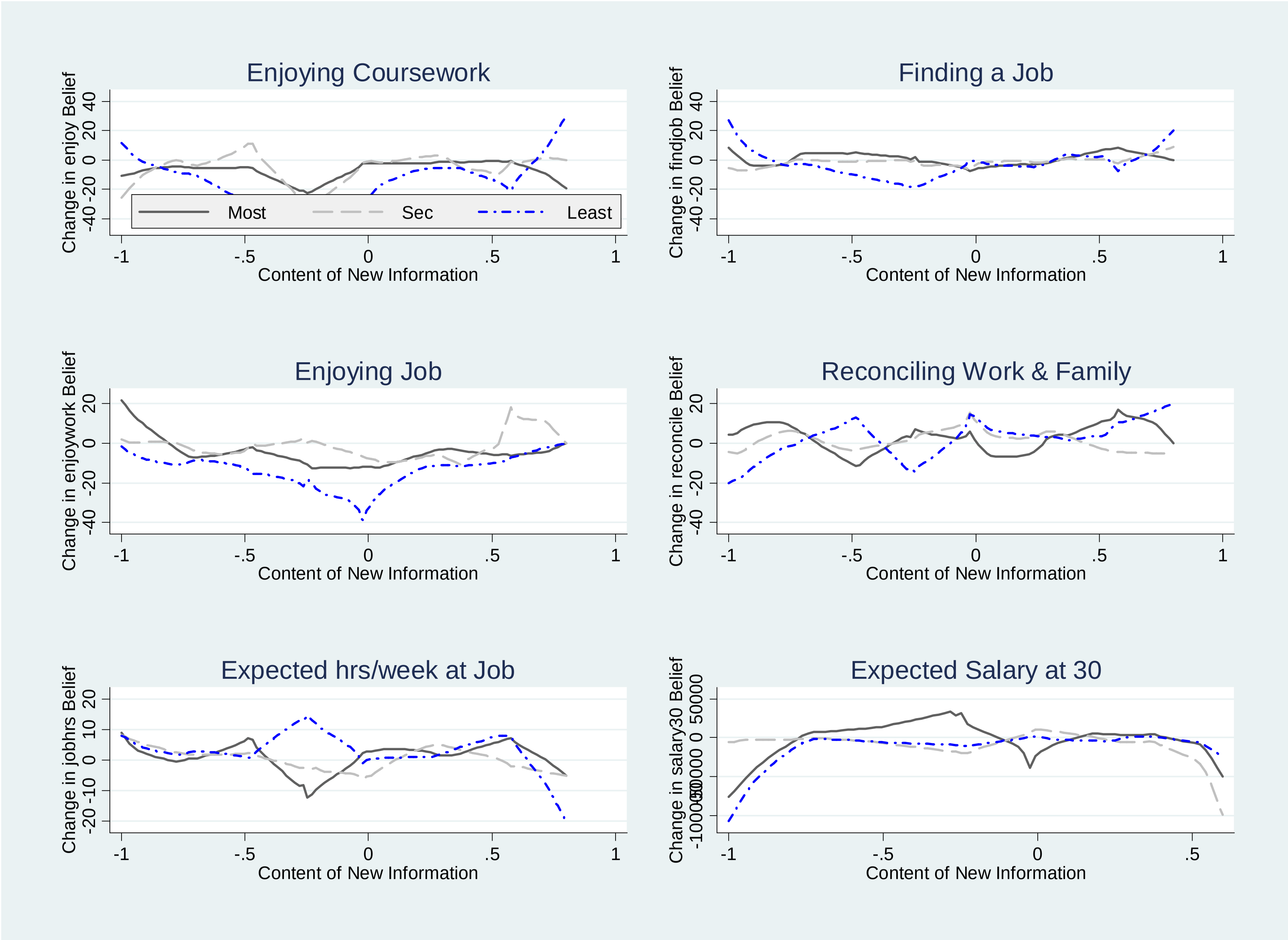

Figure A3: Local linear regressions of the change in beliefs for various outcomes (in one's *most* preferred major, *second* most preferred major, and *least* preferred major) on *new* information about ability revealed between the surveys.

Table A1: List of Majors

The following is the classification of majors into categories:

a Natural Sciences
- Biological Sciences
- Chemistry
- Environmental Sciences
- Geography*
- Geological Sciences
- Integrated Science
- Materials Science
- Physics

b Mathematical and Computer Sciences
- Cognitive Science
- Computing and Information Systems
- Mathematics
- Statistics

c Social Sciences I
- Anthropology
- Gender Studies*
- History
- Linguistics
- Political Science
- Psychology
- Sociology

d Social Sciences II
- Economics
- Mathematical Methods in Social Sciences*

e Ethics and Values
- Legal Studies*
- Philosophy
- Religion
- Science in Human Culture*

f Area Studies
- African American Studies
- American Studies
- Asian & Middle East Languages & Civilization
- European Studies
- International Studies*
- Slavic Languages and Literatures

g Literature and Fine Arts
- Art History
- Art Theory and Practice
- Classics
- Comparative Literary Studies
- Drama
- English
- French
- German
- Italian
- Spanish

h Music Studies[1]
- Jazz Studies
- Music Cognition
- Music Composition
- Music Education
- Music Technology
- Music Theory
- Musicology
- Piano Performance
- String Performance
- Voice and Opera Performance
- Wind and Percussion Performance

i Education and Social Policy[2]
- Human Development and Psychological Services
- Learning and Organizational Change
- Secondary Teaching
- Social Policy

j Communication Studies[3]
- Communication Studies
- Dance
- Human Communication Science
- Interdepartmental Studies
- Performance Studies
- Radio/Television/ Film
- Theater

k Engineering[4]
- Applied Mathematics
- Biomedical Engineering
- Chemical Engineering
- Civil Engineering
- Computer Engineering
- Computer Science
- Electrical Engineering
- Environmental Engineering
- Industrial Engineering
- Manufacturing and Design Engineering
- Materials Science and Engineering
- Mechanical Engineering

L Journalism[5]
- Journalism

∗ *Adjunct majors (these do not stand alone)*

1 Majors in the School of Music
2 Majors in the School of Education and Social Policy
3 Majors in the School of Communication
4 Majors in the McCormick School of Engineering
5 Majors in the Medill School of Journalism

Table A2: Why Do Students Switch Majors?

Reasons for dropping majors	
The initial major was too challenging	14.10[a]
	(22.62)[b]
The initial major was too easy	1.70
	(6.19)
I did not find the major interesting any more	29.80
	(28.97)
I got interested in something else	29.90
	(29.89)
My parents wanted me to change majors	0.80
	(2.63)
There was peer pressure to change majors	0.80
	(3.40)
Others	31.00
	(29.60)
Number of Observations	14

[a] Each cell is the AVERAGE contribution of the reason for switching majors. Students were asked to assign an integer between 0 and 100 to each reason so that their responses all summed to a 100.

[b] Standard deviation in parentheses.

Table 1: Sample Characteristics

Characteristics	Follow-up Survey[a] Freq.	(Percent)	Initial Survey[b] Freq.	(Percent)	Population[c] Freq.	(Percent)
	(1)		(2)		(3)	
Gender:						
Male	51	(43.5)	69	(43)	465	(46)
Female	66	(56.5)	92	(57)	546	(54)
Total	117		161		1011	
Ethnicity						
Caucasian	66	(56)	79	(49)	546	(54)
African American	10	(9)	11	(7)	71	(7)
Asian	35	(30)	56	(35)	232	(23)
Hispanic	1	(1)	5	(3)	61	(6)
Other	5	(4)	10	(6)	101	(10)
Declared Major:[d]						
Yes	61	(52)	90	(56)	477[g]	(47)
No	56	(48)	71	(44)	534	(53)
Second Major:[e]						
Yes	55	(47)	78	(48.5)	-	
No	62	(53)	83	(51.5)	-	
Average GPA:*						
Male	3.51		3.48		3.26	
Female	3.43		3.40		3.31	
WCAS Majors:[f]						
Natural Sciences	22	(19)	31	(19)	-	
Math & Computer Sci	2	(1.5)	4	(2.5)	-	
Social Sciences I	33	(28)	41	(25.5)	-	
Social Sciences II	35	(30)	48	(30)	-	
Ethics and Values	1	(1)	4	(2.5)	-	
Area Studies	8	(7)	13	(8)	-	
Lit & Fine Arts	16	(13.5)	20	(12.5)	-	

a Individuals who participated in the follow-up (second) survey.
b Individuals who participated in the initial survey.
c Population statistics for the sophomore class. (Source: Northwestern Office of the Registrar).
d Whether the respondent has declared a major at the time of the INITIAL survey.
e Whether the respondent was pursuing a second major at the time of the INITIAL survey.
f Major distribution of students. In cases where the survey respondent has more than one major in WCAS, only the first one is included. Majors that appear in each category are listed in Table A1.
g Statistic obtained from Registrar's Office at the end of the Fall 2006 quarter (during/middle of first survey).
$*$ Difference in GPAs within gender between the two surveys is insignificant (2-tailed t-test).

Table 2: Beliefs of Graduating with a GPA of at Least 3.5

Percent chance of graduating with a GPA≥3.5 in:	Current Major				Least Preferred Major			
Reported in:	Follow-up Survey		Initial Survey		Follow-up Survey		Initial Survey	
Subj. Belief:	Freq.	Cum. %	Freq.	Cum. %	Freq.	Cum. %	Freq.	Cum. %
0	1	0.9	1	0.9	6	5.8	-	0
1	-	0.9	-	0.9	-	5.8	3	2.9
2	-	0.9	-	0.9	2	7.8	-	2.9
3	-	0.9	-	0.9	-	7.8	1	3.9
5	4	4.4	-	0.9	1	8.7	2	5.9
10	1	5.3	1	1.8	5	13.6	1	6.9
12	-	5.3	-	1.8	-	13.6	1	7.8
15	-	5.3	-	1.8	1	14.6	2	9.8
20	-	5.3	2	3.7	12	26.2	4	13.7
21	-	5.3	-	3.7	1	27.2	-	13.7
25	2	7.1	1	4.6	5	32.0	1	14.7
30	-	7.1	1	5.5	4	35.9	5	19.6
33	-	7.1	-	5.5	-	35.9	1	20.6
35	-	7.1	-	5.5	1	36.9	3	23.5
40	1	8.0	2	7.3	5	41.8	6	29.4
45	2	9.7	1	8.3	2	43.7	3	32.4
50	16	23.9	4	11.9	7	50.5	10	42.2
55	1	24.8	1	12.8	1	51.5	1	43.1
60	7	31.0	9	21.1	7	58.2	8	51.0
65	4	34.5	3	23.9	2	60.2	3	53.9
68	-	34.5	-	23.9	1	61.2	-	53.9
70	10	43.4	8	31.3	6	67.0	10	63.7
73	-	43.4	1	32.1	-	67.0	-	63.7
75	15	56.6	7	38.5	3	69.9	3	66.7
76	-	56.6	1	39.5	-	69.9	-	66.7
79	-	56.6	1	40.4	-	69.9	-	66.7
80	13	68.1	13	52.3	7	76.7	5	71.6
82	1	69.0	2	54.1	-	76.7	1	72.6
85	7	75.2	9	62.4	-	76.7	5	77.5
87	-	75.2	1	63.3	-	76.7	-	77.5
88	-	75.2	-	63.3	-	76.7	1	78.4
89	-	75.2	2	65.1	-	76.7	-	78.4
90	11	85.0	10	74.3	9	85.4	9	87.3
91	1	85.8	1	75.2	-	85.4	2	89.2
92	-	85.8	2	77.1	-	85.4	-	89.2
95	3	88.5	10	86.2	7	92.2	2	91.2
96	-	88.5	1	87.2	-	92.2	-	91.2
98	1	89.4	4	90.8	-	92.2	3	94.1
99	2	91.2	2	92.7	2	94.2	2	96.1
100	10	100	8	100	6	100	4	100

Table 3: The Nature of Change in Beliefs for Outcomes

Dependent Variable: Change in belief for:	Grad in 4 Years	Grad w/ GPA $\geq$ 3.5	Enjoy Courses	Course Hrs/Wk	Parents Approve	Find Job	Enjoy Work	Work Flexible	Job Hrs/Wk	Salary at 30
Constant	1.48	-5.32***	-4.11***	-5.53***	0.39	-0.92	-4.55***	2.05	2.13	14549***
	(1.13)	(2.05)	(1.50)	(1.24)	(1.51)	(2.25)	(1.75)	(2.01)	(1.19)	(5227)
Second Pursued Major	2.36*	3.07	3.72	1.15	-0.19	-0.18	-1.37	1.82	0.097	7155
	(1.42)	(2.50)	(2.44)	(1.41)	(2.82)	(3.13)	(2.69)	(2.56)	(1.73)	(12976)
Second Preferred Major	-1.72	0.78	1.42	2.52*	-5.51*	-1.89	0.55	2.34	-1.03	-13982**
	(1.47)	(2.78)	(3.16)	(1.16)	(2.89)	(2.84)	(3.38)	(3.13)	(2.22)	(6797)
Dropped Major	-8.48*	6.84	-6.20	-0.31	-2.31	0.67	-2.01	1.98	-1.79	-20526
	(5.14)	(4.91)	(4.34)	(3.24)	(3.44)	(2.74)	(7.02)	(7.11)	(3.23)	(27206)
Least Preferred Major	-2.07	-1.23	-5.05*	5.31***	-0.76	-1.24	-8.23***	-1.45	0.45	-19453***
	(2.23)	(2.81)	(2.72)	(1.29)	(2.58	(2.74)	(2.95)	(2.87)	(1.39)	(5565)
Test of joint sig of covariates excluding the constant term	Can't Rej[a] P = .118	Can't Rej P .266	Can't Rej P = .434	Reject P = .039	Can't Rej P = .211	Can't Rej P = .778	Can't Rej P = .291	Can't Rej P = .659	Can't Rej P = .668	Can't Rej P = .183
Test of joint sig of least pref and sec pref major	Can't Rej[b] P = .199	Can't Rej P = .921	Can't Rej P = .396	Reject P = .000	Can't Rej P = .159	Can't Rej P = .493	Can't Rej P = .130	Can't Rej P = .857	Can't Rej P = .838	Reject P = .002

NOTE.–Regressions include random effects. Each of these regressions has 341 observations with 117 groups (students). The binary outcomes (all outcomes excluding coursework hrs/wk; job hrs/week; salary at 30) are on a 0-100 scale. Cluster standard errors in parentheses.

* sig at 10%; ** sig at 5%; *** sig at 1%.

[a] F-test for the joint significance of the covariates excluding the constant term. "Can't Rej": cannot reject the null that the coefficients are not significantly different from zero.

[b] F-test for the joint significance of the coefficients on the second preferred major and least preferred major (majors never pursued by the respondent).

Table 4: Shift towards the Extermities

Dependent Variable: Indicator for whether respondent's belief moves into the extreme ($\geq$90; $\leq$10)

	Grad in 4 Years	Grad w/ GPA $\geq$ 3.5	Enjoy Courses	Parents Approve	Find Job	Enjoy Work	Work Flexible
Constant	0.11***	0.10***	0.10***	0.19***	0.13***	0.12***	0.12***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Second Pursued Major	0.04	0.03	0.10*	0.03	-0.02	-0.04	0.01
	(0.04)	(0.04)	(0.06)	(0.06)	(0.05)	(0.04)	(0.05)
Second Preferred Major	-0.01	0.00	0.01	-0.02	-0.02	-0.02	0.10*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.04)	(0.05)
Dropped Major	0.03	0.18	0.04	-0.06	0.15	-0.04	0.35**
	(0.09)	(0.13)	(0.08)	(0.09)	(0.12)	(0.08)	(0.14)
Least Preferred Major	0.02	0.12**	0.06	-0.06	-0.05	0.03	0.05
	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)
Test of joint significance of covariates excluding constant	Cannot rej[a] P = .583	Reject P = .064	Cannot rej P = .179	Cannot rej P = .509	Cannot rej P = .749	Cannot rej P = .582	Reject P = .011
Test of joint significance of Least Pref Major and Second Preferred Major	Cannot rej P = .878	Cannot rej P = .147	Cannot rej P = .417	Cannot rej P = .379	Cannot rej P = .424	Cannot rej P = .946	Reject P = .054
Number of Groups	117	117	117	117	117	117	117

NOTE.– Regressions include random effects. Each of these regressions has 341 observations with 117 groups (students). The binary outcomes (all outcomes excluding coursework hrs/wk; job hrs/week; salary at 30) are on a 0-100 scale. Cluster standard errors in parentheses.

* sig at 10%; ** sig at 5%; *** sig at 1%.

[a]F-test for the joint significance of the covariates (excluding the constant term). Here can't reject the null that they are significantly different from zero.

Table 5: Updating GPA Beliefs

Dependent Variable:	Change in Spring 2008 GPA beliefs						Change in Graduation GPA beliefs					
	All			Same Major[a]			All			Same Major		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\triangle$ GPA between the surveys	37.32**	-	13.21	39.42**	-	17.21	30.15**	-	17.01	32.05**	-	14.63
	(18.57)		(22.04)	(19.40)		(22.88)	(12.88)		(15.43)	(13.61)		(16.01)
Information Content	-	14.83***	12.69*	-	14.95***	12.16*	-	9.77**	6.97	-	11.99***	9.59**
		(5.34)	(6.44)		(5.71)	(6.82)		(3.79)	(4.56)		(4.03)	(4.82)
R-Squared	0.026	0.055	0.050	0.030	0.055	0.051	0.047	0.048	0.050	0.044	0.074	0.073
No. of Observations	116	116	116	102	102	102	112	112	112	99	99	99

NOTE.– Standard errors in parentheses.

* sig at 10%; ** sig at 5%; *** sig at 1%.

[a]Sample restricted to respondents who have the same major in both surveys.

Table 6: Absolute Change in Beliefs as a Function of Uncertainty in Prior Belief

Dependent Variable: Absolute Change in belief for:	Grad in 4 years	Grad w/ GPA $\geq$ 3.5	Enjoy Courses	Parents Approve	Find Job	Enjoy Work	Work Flexible
				Entire Sample			
Constant	7.85***	13.59***	12.79***	10.23***	14.97***	15.08***	12.13***
	(1.01)	(1.09)	(0.94)	(0.86)	(1.56)	(1.13)	(1.37)
U^a	18.06***	3.53**	7.27***	9.44***	3.26*	4.41***	6.81***
	(3.28)	(1.59)	(1.63)	(1.88)	(1.85)	(1.61)	(1.74)
Observations	341	341	341	341	341	341	341
No. of Clusters	117	117	117	117	117	117	117
			Observations with non-negative revisions				
Constant	4.78***	9.56***	7.15***	6.11***	10.48***	8.68***	9.56***
	(0.61)	(1.66)	(1.14)	(0.88)	(2.14)	(1.59)	(2.13)
U	22.20***	1.79	9.87***	10.08***	5.33**	4.64**	8.73***
	(4.30)	(2.14)	(2.21)	(2.23)	(2.61)	(2.08)	(2.52)
Observations	261	169	155	217	183	152	208
No. of Clusters	108	93	92	109	94	89	103
			Observations with non-positive revisions				
Constant	7.89**	13.42***	13.15***	9.88***	14.90***	15.36***	10.38***
	(1.69)	(1.31)	(1.10)	(1.17)	(1.74)	(1.36)	(1.34)
U	10.21***	4.09*	5.69**	7.33***	0.72	5.47***	4.72**
	(4.68)	(2.14)	(2.32)	(2.53)	(2.20)	(1.94)	(2.18)
Observations	168	224	233	206	203	234	184
No. of Clusters	87	105	112	101	99	109	102

NOTE.– Each panel-column corresponds to one regression. Regressions include random effects. Each regression has 341 observations with 117 groups (students). Cluster standard errors in parentheses.

* sig at 10%; ** sig at 5%; *** sig at 1%.

[a] $U = 1$ if prior belief (belief in first survey) is ≥ 25 or ≤ 75.

Table 7: Updating in Response to New Information

Dependent Variable: The posterior belief (i.e. belief in the follow-up survey)	Dropped Mj[a]	Least Pref.	Sec Pref. Mj[b]	Second Mj[c]	Current Mj
	N=14	N=102	N=58	N=58	N=109
	Dependent Variable: New Belief about Graduating in 4 years				
Initial Belief (γ)	1.48***	0.79***	0.90***	0.73***	0.87***
	(0.269)$^{+}$	(0.031)	(0.026)	(0.038)	(0.029)
New Info (η)	0.34***	0.032	0.012	0.033***	0.03***
	(0.07)$^{+++}$	(0.020)	(0.023)	(0.010)	(0.010)
	Dependent Variable: New Belief about Graduating with a GPA of more than 3.5				
Initial Belief (γ)	0.55***	0.83***	0.86***	0.62***	0.63***
	(0.089)	(0.028)$^{+++}$	(0.028)$^{+++}$	(0.052)	(0.034)
New Info (η)	0.37***	0.10***	-0.05**	0.054***	0.11***
	(0.063)$^{+++}$	(0.017)	(0.024)$^{+++}$	(0.020)$^{+++}$	(0.016)
	Dependent Variable: New Belief about Enjoying Coursework				
Initial Belief (γ)	0.84***	0.55***	0.76***	0.53***	0.58***
	(0.083)$^{+++}$	(0.033)	(0.029)$^{+++}$	(0.057)	(0.034)
New Info (η)	0.18***	0.012	-0.094***	0.044**	0.022*
	(0.063)$^{+++}$	(0.018)	(0.024)$^{+++}$	(0.020)	(0.012)
	Dependent Variable: New Belief about Approval of Parents				
Initial Belief (γ)	1.49***	0.74***	0.93***	0.76***	0.79***
	(0.099)$^{+++}$	(0.029)	(0.032)$^{+++}$	(0.054)	(0.043)
New Info (η)	-0.068	-0.013	-0.014	-0.071***	0.014
	(0.050)	(0.018)	(0.027)	(0.023)$^{+++}$	(0.013)
	Dependent Variable: New Belief about Finding a job				
Initial Belief (γ)	0.33*	0.55***	0.66***	0.54***	0.44***
	(0.169)	(0.033)$^{+}$	(0.040)$^{+++}$	(0.048)	(0.048)
New Info (η)	0.10	0.008	-0.08***	0.056***	-0.0027
	(0.116)	(0.018)	(0.026)$^{+++}$	(0.019)$^{+++}$	(0.018)
	Dependent Variable: New Belief about Enjoying working at the jobs				
Initial Belief (γ)	0.30***	0.56***	0.75***	0.42***	0.59***
	(0.084)$^{+++}$	(0.032)	(0.032)$^{+++}$	(0.048)$^{+++}$	(0.043)
New Info (η)	0.26***	-0.034*	-0.023	0.014	-0.0046
	(0.057)$^{+++}$	(0.018)	(0.025)	(0.018)	(0.014)
	Dependent Variable: New Belief about Reconciling work and family at the jobs				
Initial Belief (γ)	0.11	0.79***	0.92***	0.40***	0.54***
	(0.206)$^{+}$	(0.030)$^{+++}$	(0.042)$^{+++}$	(0.048)	(0.038)
New Info (η)	0.60***	0.062***	-0.11***	-0.065***	-0.057***
	(0.064)$^{+++}$	(0.018)$^{+++}$	(0.030)	(0.017)	(0.015)

NOTE.– Each column within a panel corresponds to one regression. The posterior beliefs and the initial beliefs are on a scale of 0-100 for the binary outcomes. Standard errors in parentheses.

* sig at 10%; ** sig at 5%; *** sig at 1%.

$^{+, ++, +++}$Indicates coefficient statistically different from the coefficient on most pref major at 10%, 5%, and 1%, respectively.

a A major that the individual had once pursued.

b The second most preferred major for individuals without a second major.

c The individual's second major.

Table 8: Relative Importance of New Information

	Dropped Mj[a]	Least Pref.	Sec Pref. Mj[b]	Second Mj[c]	Current Mj
	N=14	N=102	N=58	N=58	N=109
Beliefs about:					
Graduating in 4 years	-0.32*+	.27***	0.12***	0.37***	0.15***
Graduating with a GPA >=3.5	0.81***	0.21****+++	0.17****+++	0.62***	0.6***
Enjoying Coursework	0.20*+++	0.81***	0.31****+++	0.89***	0.73***
Approval of Parents	-0.33****+++	0.36***	0.08****++	0.31***	0.27***
Finding a job	2.05***	0.83****+	0.51****+++	0.85***	1.26***
Enjoying working at the jobs	2.33****+++	0.8***	0.33****+++	1.40****+++	0.69***
Reconciling work and family at the jobs	7.91****+	0.26****+++	0.089*+++	1.50***	0.87***

NOTE.–Each column within a panel corresponds to one regression. Standard errors in parentheses.

* sig at 10%; ** sig at 5%; *** sig at 1%.

+, ++, +++ Indicates coefficient statistically different from the coefficient on most preferred major at 10%, 5%, and 1%, respectively.

a A major that the individual had once pursued.

b The second most preferred major for individuals without a second major.

c The individual's second major.

Table 9: Mean Deviations In Belief

	Initial Survey	
	Dropped Majors[a]	Alternative Majors[b]
	(1)	(2)
Graduate in 4 years	6.55	0.91
Graduate with a GPA ≥3.5	5.34	-0.20
Enjoy courses	9.24	0.86
Coursework hours/week	0.67	0.31
Parents approval	14.57	8.51
Find job	6.51	-0.40
Enjoy work at jobs	-0.63	5.62
Work flexible	3.39	6.42
Job hours/week	2.77	2.04
Salary at 30	55565.88	13514.47

[a]The mean deviation for outcome j for dropped majors is: $\frac{1}{7}\sum_{m=1}^{7}(\overline{b_{jm}^{D_m}} - \overline{b_{jm}^{(1-D_m)}})$, where $\overline{b_{jm}^{D_m}}$ $(\overline{b_{jm}^{(1-D_m)}})$ is the mean belief for outcome j in major m reported by respondents who dropped (never dropped) major m.

[b]The mean deviation for outcome j in alternative majors is: $\frac{1}{7}\sum_{m=1}^{7}(\overline{b_{jm}^{D_k}} - \overline{b_{jm}^{(1-D_k)}})\ \forall\ k \neq m$, where $\overline{b_{jm}^{D_k}}$ $(\overline{b_{jm}^{(1-D_k)}})$ is the mean belief for outcome j in major m reported by respondents who dropped (never dropped) major k, where $k \neq m$.

Table 10: Errors in Expectations of Starting Salary

Dependent Variable: Log Absolute Error in Beliefs about:⊕

	Initial Survey			Second Survey					
	All	Overpredictors[a]	Underpredictors[b]	All	Over	Under	All	Over	Under
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	2.86***	2.78***	2.89***	2.68***	2.62***	2.68***	2.48***	2.02***	2.55***
	(0.13)	(0.23)	(0.12)	(0.12)	(0.22)	(0.13)	(0.17)	(0.43)	(0.16)
Dropped Major	0.26	0.57*	-0.13	0.53*	0.08	0.58	0.55*	0.10	0.58
	(0.21)	(0.32)	(0.23)	(0.27)	(0.40)	(0.40)	(0.29)	(0.41)	(0.42)
Least Preferred Major	0.21	0.23	0.23*	0.32**	0.10	0.36***	0.33**	0.12	0.36***
	(0.14)	(0.29)	(0.13)	(0.13)	(0.28)	(0.11)	(0.14)	(0.29)	(0.12)
Second Pursued Major	-0.19	-0.78*	0.16	0.12	-0.09	0.16	0.16	0.04	0.17
	(0.21)	(0.43)	(0.12)	(0.15)	(0.31)	(0.12)	(0.14)	(0.31)	(0.12)
Second Preferred Major	-0.06	-0.40	0.22	0.22	0.42	0.04	0.23	0.55	0.06
	(0.19)	(0.38)	(0.14)	(0.17)	(0.38)	(0.14)	(0.17)	(0.39)	(0.15)
Abs error in initial survey							0.07	0.19	0.05
							(0.05)	(0.12)	(0.04)
Test of joint sig of covariates	Can't Rej[c]	Can't Rej	Can't Rej	Reject	Can't Rej	Reject	Reject	Can't Rej	Reject
excluding constant term	P = .683	P = .704	P = .298	P = .032	P = .603	P = .059	P = .028	P = .414	P = .067
Test of joint sig of least pref	Can't Rej[d]	Can't Rej	Reject	Reject	Can't Rej	Reject	Reject	Can't Rej	Reject
and sec pref major	P = .936	P = .325	P = .077	P = .077	P = .982	P = .011	P = .049	P = .758	P = .011
Resp. Random Eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	341	147	195	341	124	217	335	120	215
No. of Clusters	117	77	89	117	73	104	117	72	104
R-squared	0.0155	0.0544	0.0158	0.0157	0.0146	0.0422	0.0243	0.0391	0.0505

NOTE.–Estimates correspond to OLS estimation. Cluster errors in parentheses.

* sig at 10%; ** sig at 5%; *** sig at 1%.

⊕Dep. var is $\ln\left|\frac{\overline{s_{im}}-s_{obs\_m}}{s_{obs\_m}}*100\right|$; $\overline{s_{im}}$ is respondent's belief of the avg. salary of the last NU graduating cohort in major m, and s_{obs_m} is the actual avg. salary of the graduates in m.

$a(b)$ sample restricted to students who report expectations higher (lower) than realizations, i.e., $\overline{s_{im}} > s_{obs\_m}$ ($\overline{s_{im}} < s_{obs\_m}$).

c F-test for the joint significance of the covariates excluding the constant term.

d F-test for the joint significance of the coefficients on the second preferred major and least preferred major (majors never pursued by the respondent).