References

Becker, W.E., Watts, M. and Becker, S. R. (2006) (Eds) *Teaching Economics: More Alternatives to Chalk and Talk*, Cheltenham: Edward Elgar.

Hazlett, D. (2007) 'A Classroom Investment Coordination Experiment', *International Review of Economics Education*, 6, 1, pp. 63–76.

Kolb, D. A. (1984) 'Experiential Learning: experience as the source of learning and development', Englewood Cliffs: Prentice Hall.

Lo, M., Wong, S. and Mixon, F. G. (2008) 'Ranking Economics Journals, Economics Departments and Economists using teaching-focused research productivity', *Southern Economic Journal*, 74, 3, pp. 894–906.

Reimann, N. (2004) 'First-Year Teaching-Learning Environments in Economics', *International Review of Economics Education*, 3, 1, pp. 9–38.

Social Learning and Course Choice

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Abstract

We use a broad sample of students to examine the course selection process and find evidence of social learning from peers. We also find that as the number of times students solve the course selection problem increases, they rely less on social learning and more on their own experience, limiting the potential for herd behaviour. Our results give insight to instructors about the reasons why students may be in their classes and suggest that information about courses and help in evaluating this information is especially important for students early in their college careers.

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Introduction

The course choice process is a complex one. Yet decisions about the classes students take are important; many students report that specific classes they have taken in college have been transforming experiences, causing them to change the way they think about themselves dramatically, (see, for example, Pascarella and Terenzini, 1991 or Light, 2001). Several authors have shown that class selection and choice of a college major are important for occupational choice and its implications for future earnings. In addition, instructors of economics who want to motivate students to succeed need to understand why and how the students in their classes chose to be there.[1]

We analyse the class selection process, presenting evidence on exactly what factors and sources of information are considered in this decision. Because we believe that the decision to choose classes is actually quite a complicated one undertaken with imperfect information, we appeal to a theoretical framework to guide our empirical analysis. Although we do not present a formal theoretical model, our work is based on the premise that students maximise utility and select classes that are a good match for their skills and interests to achieve this goal. Indirectly, future income and/or grades may enter the student's evaluation of the match, but our approach assumes that the student's evaluation of the match takes into account all factors that may affect utility and that these factors are not limited to easily observed outcomes such as grades or income.

We draw on the social learning literature in which individuals base their decisions on others' behavior to take account of the facts that individual optimisation is complex and the learning period required to understand the problem and solve it optimally is lengthy.[2] This framework is particularly relevant for the course selection process that undergraduates undertake, undergraduates typically have fewer than eight periods of experimentation in order to learn what classes best suit their skills and interests. Furthermore, experimentation is costly as the opportunity cost of a bad course match is very high.

An interesting result of the social learning literature is that social learning can lead to herd behaviour – an inefficient outcome in which individuals ignore their own personal signals in favour of the collective wisdom of the group (see for example, Banerjee, 1992). While we find some evidence that students rely on social learning, we do not find that this process converges to herd behaviour. Interestingly, our results suggest that herd behaviour may not be an outcome of a social learning process if individuals making decisions rely less on social learning as they gain experience.

Our work is related to a growing literature on peer effects in higher education. Zimmerman (1999), Sacerdote (2001), and Winston and Zimmerman (2003) find evidence that students are influenced by the academic strength of roommates randomly selected for them in the first year of college. Our work complements this finding by suggesting one channel through which peers impact academic choices. In recent work, however, Arcidiacono and Nicholson (2005) find little evidence of peer effects in choice of specialisation in medical school. They argue that the high level of maturity of medical school students may account for the non-existent peer effects. In a similar vein, we suggest that as students mature, they rely less on peers in making academic decisions.

As explained in more detail below, we use data from a broad sample of students and describe the course selection process, with particular emphasis on examining how students with more college experience behave relative to those with less

experience. We also explore the types and sources of information that lead to better decisions. Consistent with a learning model, we find that students with more years of college experience select courses that are a slightly better match. However, as they gain experience, the information sources they consult change. Furthermore, we also find evidence for a social learning process: students rely heavily on advice from peers in selecting courses.

Our work is also related to that of others who have studied the course choice process more generally (Sabot and Wakeman-Linn, 1991; Schuhmann and McGoldrick, 1999). Unfortunately, previous work on this issue is limited, most likely due to the difficulty of assembling large and comprehensive data sets to study this complex problem. Our study contributes to this literature on the student decision process by estimating a structural model with a rich data set of student attitudes, characteristics and decision outcomes.

Our results and methods are discussed in the next four sections. First we describe our survey methods, then we present the data we collected, explain our estimation results and finally conclude.

Survey methodology

Our data collection process contained two steps. In the first step we ran focus groups of students with different years of experience in college. We then used what we learned in focus groups to design a survey that allowed us to collect systematic information about course choice from a broad sample of students. We surveyed students in all disciplines; all of our data are collected from a single institution, a highly selective residential liberal arts college in the Northeastern United States with approximately 1800 undergraduate students. Thus, our conclusions about the relative importance of specific information sources may be institution specific. However, because most of our main conclusions are drawn by comparing the behaviour of third and fourth year students with that of first and second year students, our results about how the course choice process evolves as students mature may be less influenced by institution specific factors. Moreover, because this institution shares characteristics with other selective liberal arts colleges, the results may generalise at least to students at this type of institution. For example, like other small colleges, this institution is characterised by small classes (the vast majority have 40 students or less) and close student/faculty interaction. Nonetheless, it is the case that to the extent that institution-specific factors influence the entire process and the costs and benefits of social learning, generalising our results should only be done with caution.

We ran six focus groups of approximately six to eight students each immediately following the preregistration period. We segregated the focus groups by class year to allow for the possibility that the course selection process for first-year students differed from that of the rest of the students because the first-year students have less college experience.

We asked two basic questions in these focus groups: 1) What factors influence your decision to take a course? and 2) What information sources do you use in selecting courses? As expected, the results from the focus groups indicated that students consider a variety of factors when signing up for a course. For example, some are exploring a possible major, some are meeting various requirements, and others are looking for opportunities to take courses that 'looked interesting' or that were not offered to them in high school.

Students also had a variety of methods for choosing courses that they would like, but overall, the process described by the first-year students seemed to be a very hit-and-miss strategy. A few of the first-year students exhibited behaviour that exploited the information already gathered in the first semester, intentionally taking another course with a professor whom they liked from the Fall semester. Others described a process that focused more on exploring for new information; some reported deciding on their courses while waiting in line to register and looking through the course catalogue for courses which sounded 'fun' or 'interesting'.

Students also used information gathered by peers, consistent with a social learning process. Both the first-year students and the students from the other three class years stated that the informal grapevine was very important in selecting a course based on the professor; however, some of the upper-class students expressed increased sophistication in evaluating this information. First-year students reported signing up for classes with popular professors, but did not know exactly why professors were popular. Some of the upper-class students also reported that information from peers about professors and classes was important, but they seemed more discriminating in whom they asked for advice and how they interpreted it. One upper-class student explained, for example, that he sought advice from other students who were 'more like me'.

Although we talked to a relatively small number of students in the focus groups, we were able to identify repeated themes and issues to be followed up on in our broader survey. In the second step of our data collection process, we used the results from our focus groups to develop a questionnaire that was distributed in a broad range of classes in the Spring and Fall 2002 semesters. The survey elicited information about general student characteristics, the reasons why students took

the course in which they filled out the survey, and the sources of information they consulted in making their course choice. The survey also contained a question about how well students thought the course matched up with their skills and interests.[3] Surveys were distributed at least two-thirds of the way through the semester to allow students to obtain enough experience with the course to make an assessment of their choice. In total, we have responses from approximately 1000 students in 60 different classes.

A common criticism of surveys of this nature is that they are subject to selection bias. Specifically, one might be concerned that because we are only surveying students who are still in the class about two-thirds of the way through the semester, we do not observe students who dropped the class prior to the observation date. However, it is important to note that our study is not an examination of the preregistration process – it is a study of how students choose the classes that they actually complete. To the extent that a student drops one class and adds another, the fact that we survey a broad sample of classes should ensure that we are including several students who have dropped one class but added the class in which the survey was conducted.[4]

Data

Descriptive statistics are in Tables 1A, 1B, and 1C. Table 1A summarises the overall student and course characteristics, Table 1B provides descriptive statistics for variables measuring the importance of factors in registering for courses, and Table 1C provides summary statistics for the variables measuring the different sources of information used by students.

A striking statistic in Table 1A is the average for the variable MATCH of 3.78. This measures the extent to which students believe that the course was a good choice. Specifically, students were asked to rate the extent to which they agree with the statement 'This course was a good match for my skills and interests'. A higher rating means that students agreed more strongly with this statement. Given the complexity of the problem that students solve in searching for courses, an average close to 4 indicates that students are actually remarkably successful in selecting courses. Average values for MATCH vary slightly by class year. Consistent with a learning model, third and fourth year students reported having the highest values for MATCH, (average 3.89), while first and second year students reported lower values (average 3.76). Of course, skills and interests are not the same thing and some students may feel that a course is a good match for their interests but not their skills or vice versa. By asking the question in this way, we are asking the student to weigh the importance of skills vs. interests in determining the match

Table 1A: Descriptive statistics, overall student and course characteristics

Variable	Jr./ Sr. Average – First Year/ Soph. Average	Mean	Std. Dev.	Min	Max	No. Obs.	Definition
Student Characteristics							
COLLEXP		1.85	1.36	0	4	959	years of college experience
MATCH	.13**	3.78	1.00	1	5	952	course was a good match 1=strongly disagree, 5=strongly agree
RELGRADE	.02**	1.02	0.06	0.75	1.23	771	Expected grade in course/GPA
TAKEAGAIN	.06	3.23	1.31	1	5	899	want to take more courses like this one 1=strongly disagree 5=strongly agree
Class/Instructor Characteristics							
CLASSAVG	.01**	1.02	0.03	0.96	1.09	936	Class average of expected grade/GPA
INSTREXP	2.27**	11.09	9.68	1	43	942	instructor years of experience at college
INSTRGENDER	.12**	0.43	0.49	0	1	949	instructor gender, 1=female
LEVEL	90**	175	85.72	100	400	963	level of course, 100 to 400
NOSTUDENTS	–3.5**	27.86	14.99	2	60	963	number of students registered in course

Sample includes observations from 60 classes in Arts, Humanities, Science and Social Science disciplines.

** Difference in means is significant at the 5% level.

rather than imposing an exogenous weight ourselves. Though statistically significant, the difference between more experienced and less experienced college students is rather modest at only 13% of the standard deviation for MATCH. An alternative hypothesis that would explain slightly better course matches for third and fourth year students vs. first and second year students is that these upperclass students are more likely to be in a class related to their major, a field in which they have a comparative advantage. However, our data do not support this hypothesis: we find no evidence that students with more college experience are more likely to be in classes because of their major.

As will become apparent, MATCH is the primary variable that we use to assess the optimality of the course choice. It is important to note at the outset that this measure relies on students' own evaluation of the match of skills and interests presented by a particular course. One could justifiably argue that a good education consists of many courses in which students feel that their skills and interests are challenged. Therefore, it will be important in our empirical specification to control for the rigour of the class to mitigate the concern that we are simply identifying courses that students found to be enjoyable or easy.[5] Another limitation of this measure is that it does not directly consider economic consequences of course choice. Although in a liberal arts setting it is more difficult to argue that one course increases human capital more than another, to the extent that there are economic consequences of the course choice, they are only indirectly measured through the students' self-assessment of how well the course matched their interests.[6] Finally, it is important to realise that this key variable is a subjective judgement on the part of the student. While others have found evidence of overconfidence in estimating performance in a class, this variable is not subject to the same criticism because it is not a measure of performance, but rather satisfaction with the class.[7] Nonetheless, we are cautious in interpreting our results as relating to students' beliefs that they have made a good course choice.

Continuing to focus on Table 1A, we note that, on average, students in our survey expect to do better in the course in which they filled out the survey than they had in the past, as indicated by the average of RELGRADE being higher than one. RELGRADE is the ratio of the grade students expected to earn in the class to their self-reported GPA from previous semesters. While this average of greater than one may be evidence of overly optimistic students, it is consistent with a general trend of students earning higher grades as they progress through college that is observed for the population as a whole. Of course, if we use grades earned as a signal of a good course choice decision on the part of the student, this overall trend is also indicative of a learning model in which students learn how to make better course choices as they progress through college.

Table 1B provides a summary of the factors that influenced students' decisions to take the specific course in which they filled out the survey. The factors are listed in order of importance, with the factor with the highest average response listed at the top. The responses for all factors ranged from the minimum of 1 to a maximum of 5, indicating that each of these factors was either very important or not at all important to at least one student in the sample. However, interest in the subject (INTEREST) was by far the most important factor for students registering for a course. The professor's reputation and the desire to diversify course loads were also important factors in student decision making, while satisfying distribution requirements, taking classes with friends or scheduling conflicts were factors that had less importance to the average student. Notably, college experience does not make a difference in the importance of most of these factors. Among the four most important factors in selecting courses, only importance of professor's reputation varied by college experience, with third and fourth year students having an average of 3.24 and first and second year students averaging 2.58.

Table 1C summarises the importance of sources of information that students used in the course selection process. As above, all sources were rated as either very important or not at all important by at least one student. However, the relatively low averages for even the most popular source of information indicate that students use a variety of means of accessing information. It also suggests that most students rely primarily on only a few sources of information for choosing courses. The most popular sources of information were the catalogue, academic advisors, previous experience with the subject or experience during the first week of classes. The importance of these factors, of course, is at odds with a social learning process in which students learn from others with similar experiences about how to make course selections.[8] The descriptive statistics in Table 1C suggest some differences between the sources of information consulted by students with more experience with the course choice process and those consulted by students with less. In particular, the positive and significant differences in means for the variables measuring the importance of prior experience with the subject (KNOWSUB), with the professor (KNOWPROF), or with a discussion with the professor (PROFDISC) suggest that older students rely more on their own previous experience and evaluations to make decisions. On the other hand, the negative and significant differences in means for the variables measuring the importance of advisors, family, high school teachers, high school experiences and RAs suggest that younger students who do not have that experience draw more heavily on advice from others. All students, however, seem to rely equally on peers for information about courses. We should note that the phrasing of the survey question implies that 'peers' in our data are the student's friends, not necessarily other students in the same class.

Table 1B: Descriptive statistics, importance of factors in registering for taking course

Variable	Jr./ Sr. Average – First Year/ Soph. Average	Mean	Std. Dev.	Min	Max	No. Obs.	Definition
INTEREST	.05	4.00	1.05	1	5	960	interest in subject
DIVERSIFY	–.11	2.90	1.34	1	5	958	diversifying schedule
PROFREP	.66**	2.76	1.47	1	5	956	professor's reputation
WORKLOAD	.13	2.71	1.26	1	5	959	keep workload manageable
TIMFORGRADE	.16**	2.69	1.22	1	5	959	amount of time needed for a good grade
MAJREQ	–.08	2.65	1.65	1	5	959	fulfilling major/minor requirement
TIME	.02	2.49	1.29	1	5	960	meeting time of class
JOB	–.14	2.24	1.32	1	5	959	help in doing or getting job
DISTREQ	.03	2.04	1.44	1	5	958	fulfilling distribution requirement
FRIEND	.34**	1.63	1.08	1	5	961	friend also taking class
SCHEDULE	–.07	1.59	1.11	1	5	955	scheduling conflicts with first choice

All variables are measured on a scale of 1 to 5 with 1 indicating not important and 5 indicating very important. Sample includes observations from 60 classes in Arts, Humanities, Science and Social Science disciplines.

** Difference in means is significant at the 5% level.

Table 1C: Descriptive statistics, importance of information sources

Variable	Jr./ Sr. Average – First Year/ Soph. Average	Mean	Std. Dev.	Min	Max	No. Obs.	Definition
CATALOGUE	–.13	2.90	1.33	1	5	954	course catalogue
ADVISOR	–.36**	2.33	1.37	1	5	955	academic advisor
KNOWSUB	.57**	2.23	1.44	1	5	950	prior experience with subject
FIRSTWEEK	–.18**	2.19	1.37	1	5	949	experience first week of classes
HSEXP	–.59**	2.10	1.36	1	5	955	high school experience
PEERSYES	.05	2.04	1.31	1	5	956	peers who have taken the class
SYLLABUS	.07	1.95	1.25	1	5	942	syllabus or other course materials
KNOWPROF	.77**	1.76	1.36	1	5	952	prior experience with professor
FACULTY	.01	1.71	1.15	1	5	956	faculty other than academic advisor
PROFDISC	.24**	1.68	1.18	1	5	953	discussion with professor
FAMILY	–.26**	1.68	1.10	1	5	955	family members
PEERSNO	.07	1.39	0.83	1	5	956	peers who have not taken the class
HSTEACH	–.19**	1.28	.757	1	5	955	high school teacher
RA	–.10**	1.20	0.58	1	5	955	an R.A. or Orientation Leader

All variables are measured on a scale of 1 to 5 with 1 indicating not important and 5 indicating very important. Sample includes observations from 60 classes in Arts, Humanities, Science and Social Science disciplines.

** Difference in means is significant at the 5% level.

For many of the variables reported in Tables 1A, 1B and 1C, the data are ordered, but categorical. To confirm that our overall conclusions regarding the differences between students with more experience and those with less are robust, we also compared the proportions of third and fourth year students who selected each response to the proportions of first and second year students that selected each response. Statistically significant differences appear in Table A of the Appendix. Although there are a few additional significant differences in response rates of more and less experienced students, our overall conclusions are reinforced by this analysis. Specifically, students with more college experience report in greater proportions that the course is a good match and that professor reputation and interest in the subject were important considerations in taking the class, but we find no statistically significant differences in responses regarding the importance of advice from friends in selecting the course. In the next section we use our data to estimate a structural model that gives some insight about how students use this information to select courses.

Structural model and results

We are ultimately interested in describing the course selection process and understanding what factors are associated with students making better choices. Social learning theory gives us two testable hypotheses: 1) if learning occurs, then students with more experience choosing courses should make better choices, and 2) if any of the learning is social, then students should use the experience of their peers to help inform their decision. The descriptive statistics presented above already provide evidence in favour of the first hypothesis; and, in this section, we investigate how this result occurs and the role that social learning plays in generating it.

To explore these hypotheses, we first use the students' own self-assessment of the quality of the match of their skills and interests as the dependent variable and examine the effects of the importance of various factors in selecting the course as well as the effects of using different sources of information. As mentioned above, we are particularly interested in examining the effect of college experience on the quality of the match and the use of peer experience in the decision process to determine if and how students learn about themselves and the course selection process while they are in college.

Based on our feedback from focus groups and the descriptive statistics presented in the previous section, we believe that a student's interest in the subject as well as a professor's reputation may be important factors in explaining the quality of the match. Our discussions with students suggest that a number of other course characteristics and reasons for taking the course may also be important in determining students' assessment of the quality of the match. Thus, the relationship of primary interest can be expressed as

$$MATCH_i = \beta_o + \beta_i\, INTEREST_i + \beta_2\, PROFREP_i + \beta_3\, COLLEXP_i + \beta_4 X_i + \varepsilon_i \qquad (1)$$

where MATCH is one of two different measures of the optimality of the course choice. The primary measure we focus our discussion on is the response to the statement: 'This course was a good match for my skills and interests'.

The remaining variables in our estimation are as follows. INTEREST is the importance of interest in the subject in choosing the course, PROFREP is the importance of the professor's reputation in choosing the course, and COLLEXP is the number of years of college completed prior to the current semester. While it may be obvious why interest in the subject may lead to a good match, professor's reputation may also affect the quality of the match if professors with better reputations have them in part because they are better able to teach courses that appeal to a broad range of students, thus increasing the likelihood that any individual student believes the course is a good match. The control variables in the MATCH equation, X, include the importance of several factors in taking the course: satisfying a distribution requirement, a desire to diversify courseload, taking a class because a friend is taking it, taking a class because of the time it is offered, taking a class because students could not get into their first choice, the grading standards of the instructor as measured by CLASSAVG, and taking a class because of the expected workload.[9] The only source of information directly included in the MATCH equation is experience in the first week of class because that represents direct experience with the class and is likely to be highly correlated with the student's evaluation of the class later in the semester. All of these variables may affect the student's assessment of the quality of the match. We also control for the number of students in the course, hypothesising that students in smaller classes may be more likely to feel that the class suited them personally.

In formulating the specification to be estimated, we treat the importance of professor reputation (PROFREP) and interest in the subject (INTEREST) differently than the rest of the explanatory variables because these variables, which arguably rely on more subjective assessments of the students, may be endogenous. Specifically, we are concerned that there may be omitted factors specific to the students that explain the importance of the professor's reputation and interest in the subject as well as match, making estimation of Equation 1 by OLS inconsistent. In fact, this conjecture is supported by evidence from two different Hausman tests. First, a Hausman test rejects the exogeneity of INTEREST and PROFREP, indicating that an instrumental variables estimation is necessary (p-value of 0.0004). We use a second Hausman test to evaluate whether the remaining explanatory variables are also endogenous. These results find no evidence of endogeneity of the remaining explanatory variables, providing further support for our reasoning.[10] Therefore, we estimate a system of three equations, with the first explaining the quality of the match, the second exploring the determinants of the importance of professor's reputation, and the third examining factors affecting the importance of student interest in the subject. To gain efficiency, we estimate via 3SLS rather than 2SLS. Our structural model is summarized below.

$$\begin{aligned} MATCH_i &= \beta_0 + \beta_1\, INTEREST_i + \beta_2\, PROFREP_i + \beta_3\, COLLEXP_i + \beta_4 X_i + \varepsilon_i \\ PROFREP_i &= \alpha_0 + \alpha_1 Y_i + \alpha_2 COLLEXP_i + \zeta_i \\ INTEREST_i &= \gamma_0 + \gamma_1 Z_i + \gamma_2 COLLEXP_i + \xi_i \end{aligned} \qquad (2)$$

The equation for PROFREP contains the number of years of college experience (COLLEXP) to test the idea that students' approach to the course choice decision is refined as they gain more experience making it. It also contains two variables to test the hypothesis that students rely on the experience of their peers, PEERSYES and PEERSNO. Students who have high values of PEERSYES indicated that peers who have taken the class they are considering were an important source of information and students with high values of PEERSNO indicated that peers who did not take the specific class they were considering were an important information source. If students learn about professors' reputations through a social learning process, the coefficient on PEERSYES should be positive and significant. To the extent that other students who have not taken the class have had relevant experiences with a specific professor, the PEERSNO variable should also enter positively and significantly. However, the correlation may be weaker if these students have less relevant experience. Y contains additional control variables that might influence the importance of professor's reputation in the course selection process. We include in Y sources of information that students use: the student's RA or orientation leader, the student's academic advisor, other faculty, previous experience with the professor, a discussion with the professor, experience during the first week of class, and the course syllabus. Y also includes characteristics of the course and instructor that may affect students' perception of the professor: instructor experience, instructor gender, the level of the course, and the average relative grade for everybody in the class. Finally, we include a measure of the importance in the course decision process of the amount of work that students expected to do to get the grade they wanted.

The equation for INTEREST is formulated in a similar manner. It includes years of college experience, the importance of advice from peers who have taken the class, and the importance of advice from peers who have not taken the class to test our hypotheses about learning about the course selection process and social learning. Our focus groups clearly gave us indications that peers were an important source of information about individual professors; moreover, to a lesser extent, they also indicated that friends were a source of information about 'interesting courses'. We look for more formal evidence of these effects by including these two variables that measure the importance of information obtained from peers in the INTEREST equation.

The control variables in Z contain factors that affect the importance of student interest in the subject in selecting the specific course. As above, we include several variables that measure the importance of different sources of information (RA or orientation leader, family members, academic advisors, other faculty, high school teacher, discussion with the professor, course syllabus, course catalog, experience in the first week of class, or previous experience in college with the subject). We also include information about the reasons why a student took the class (because it was important to their career, satisfying a distribution requirement, or satisfying a major requirement). Although the PROFREP and INTEREST equations share many independent variables, they differ in that the PROFREP control variables attempt to control for factors that may influence a student's assessment of a professor, while the control variables in INTEREST include factors that are related to the topic of the class rather than the specific professor teaching the course. For example, importance of advice from family is included as a control variable in INTEREST but not PROFREP because family members most likely do not have knowledge about specific professors.

PROFREP and INTEREST are not direct measures of the professor's reputation and student interest; rather, they measure the importance of these factors in student course choice. Nonetheless, as we define our empirical specification and interpret our results, we note that these variables are indirect measures of the professor's actual reputation and the students' actual interest in the subject: students who say that either interest in the subject or a professor's reputation were important criteria in choosing the class are unlikely to be in a class in which they have a low assessment of the professor's reputation or a low level of interest in the class. Thus, in our discussion and interpretation, we assume that these variables are highly correlated with the professor's reputation and a student's interest in the subject.

The results in Table 2 suggest that students who placed great importance on their interest in the subject and the professor's reputation are much more likely to have made a good course choice. Not surprisingly, students in larger classes and students who took a class because scheduling conflicts prevented them from taking their first choice were less likely to say that the course matched up well with

Table 2: 3SLS results

	MATCH	**PROFREP**	**INTEREST**
PROFREP	.129** (3.04)		
INTEREST	.629** (7.47)		
Information Sources			
PEERSYES		.161** (5.05)	–.021 (0.85)
PEERSNO		.051 (0.99)	–.097** (2.40)
RA		–.120 (1.50)	–.029 (0.43)
ADVISOR		.055* (1.69)	–.016 (0.63)
FACULTY		.008 (0.21)	.014 (0.43)
KNOWPROF		.397** (11.44)	
PROFDISC		.104** (2.49)	.059* (1.87)
SYLLABUS		.017 (0.48)	.030 (1.06)
FIRSTWEEK	.073** (2.90)	.064** (2.00)	.014 (0.53)
HSTEACH			–.000 (0.00)
HSEXP			.072** (2.58)
KNOWSUB			.153** (6.31)
CATALOG			.0.142** (5.78)
FAMILY			.043 (1.32)
Student/Course Characteristics			
DISTREQ	–.014 (0.61)		–.123** (5.35)
MAJREQ			.006 (.030)
DIVERSIFY	–.015 (0.66)		
FRIEND	–.027 (0.85)		
TIME	.005 (0.19)		
SCHEDULE	–.075** (2.43)		
WORKLOAD	–.062 (2.37)		
NOSTUDENTS	–.006** (2.75)		
COLLEXP	–.062** (2.29)	.074* (1.94)	.032 (1.12)
INSTRGENDER	–.226** (3.32)		
INSTREXP	.011** (2.60)		
CLASSAVG	3.639** (2.74)	–1.460 (0.94)	
LEVEL		.002** (3.80)	
TIMFORGRADE		.157** (4.54)	
JOB			.128** (4.77)
R^2	.22	.39	.21
Number of Observations	839	839	839

** Significant at the 5% level; *significant at the 10% level.
Absolute values of z-statistics are to the right of the coefficient in parentheses.
All equations include a constant

their skills and interests. The coefficient on college experience in the MATCH equation is actually negative and significant. However, as we discuss below, because college experience impacts some of the other independent variables in this estimation, we do not conclude that students with more experience overall make inferior course choices.

The remaining two equations in this system also provide some insight into the course choice process because they explore the determinants of PROFREP and INTEREST, by far the two most influential independent variables in the MATCH equation. (A 1 standard deviation increase in PROFREP or INTEREST increases MATCH by 0.19 and 0.66, respectively.) The second equation identifies class and student characteristics for students who rate the professor's reputation as a more important reason for taking the class. We can separate the independent variables in this estimation into two categories. One category contains the variables that attempt to identify the sources of information used by students who rate professor's reputation as important (peers, other faculty, advisor, discussion with professor, previous experience with the professor, experience in the first week of classes). The second category contains variables that measure course and instructor characteristics more likely to be associated with students who consider the professor's reputation to be important.

In terms of information sources regarding a professor's reputation, these results provide two pieces of evidence in support of a social learning process. First, the coefficient on PEERSYES suggests that peers who have taken the class are an important source of information. Second, students with more years of college experience are more likely to be in a course because of the professor's reputation. Because professor's repuation is also positively linked to MATCH, this provides evidence for a channel through which experience allows students to make better choices.

The remaining significant coefficients in this equation tell us that students who consider the professor's reputation also are more likely to weigh the advice of their academic advisor more heavily in the course selection decision. However, there is also evidence that students rely heavily on their own judgements regarding professors. Previous experience with the professor, discussions students have with the professor, and experience in the first week of class are also important to students who want to take classes with professors because of their reputation. These results suggest that students are learning both from others and from their own experiences.

In terms of characteristics of classes/professors that attract students who think the professor's reputation is important, we find that higher level classes (LEVEL) are more likely to have students in them who are there because of the professor. This could be explained by the fact that as students take more courses in one department, they are more likely to know more about the professors in that department. Or perhaps, as the level of the course increases, some students might believe that the qualities of the professor are more important to their success. The insignificance of the coefficient on grading standards for the class, CLASSAVG, suggests that it is not the professor's reputation for grades that is important; however, the positive and significant coefficient on TIMFORGRADE does hint that expected grades affect student course choice in a more indirect way. What matters is not the actual grade received, but how much effort it takes to obtain the desired grade. Instructors with more teaching experience have more students in their classes who are there because of their reputation, but the negative coefficient on instructor gender indicates that female instructors are less likely to have students in their class because of their reputation; there may be some gender bias in either the evaluation of female instructors or the way in which professors' reputations are established among students.

The third equation in our system looks at the factors associated with students who are taking classes because they are interested in the subject. As above, we can divide the independent variables in this estimation into the two categories of sources of information about the course and characteristics of the course or student. The results from this estimation provide no evidence of a social learning process: students who take classes because of their interest in the subject are actually less likely to consult peers who have not taken the class. Thus, interest in a subject may be a characteristic that students develop relatively independently. This conjecture would be consistent with Sacerdote (2001) who finds that peer effects were not significant in explaining choice of college major. In fact, one of the most important information sources for students who are taking a class because of their interest is the course catalogue. This is consistent with our focus group findings in which students described looking through the catalogue for courses that looked 'fun' or 'interesting'. Students are also more likely to be in a class because of their interest in the subject if they think the course is important for their future career (JOB) or if they have talked to the professor previously (PROFDISC). Additionally, previous experience in the subject matter is important, as evidenced in the positive coefficients on high school or college experience with the subject (HSEXPER and KNOWSUB, respectively).

Our results are robust to a number of different estimation strategies. In Tables B and C of the Appendix, we report two-stage least squares estimation results and ordinary least squares results. The results in these tables are qualitatively similar to those discussed above. In addition, recognising that our dependent variables in this initial estimation are measured on a scale of 1 to 5, we estimate the equations in our system individually as ordered probits and obtain qualitatively similar results. We explore an alternative specification in which our main variables of interest, PEERSYES, PEERSNO and COLLEXP, enter as separate dummy variables rather than continuous variables. Wald tests, however, cannot reject the restriction we have imposed in the estimations reported in the paper that all the coefficients on the dummy variables are equal except for two cases (PEERSYES in the PROFREP equation and PEERSNO in the INTEREST equation). Even in these two cases, our qualitative conclusions remain unchanged. Therefore, we present results from the more parsimonious model. While we conclude that our results are generally robust, a caveat to this conclusion, of course, is that our data may contain measurement error. Unfortunately, we do not have valid instruments to address this issue econometrically.

One broad conclusion that can be drawn from the coefficients on importance of advice from family, academic advisors, peers who have taken the class and other faculty is that students in classes because of their interest in the subject rely little on other people for advice. The social learning effects we find in the results in Table 2 are relatively modest. For example, a 1 standard deviation increase in importance of advice from peers who have taken the class, PEERSYES, (SD = 1.31) results in a 0.20 increase in PROFREP and explains only a small part of the variation in this variable. A slightly more important effect is obtained through the variation in previous experience with professor, KNOWPROF, or previous experience with the subject, KNOWSUB. For example, a 1 standard deviation increase in KNOWPROF (1.36) results in a 0.51 increase in PROFREP (about one-third of a standard deviation of PROFREP) and a one standard deviation increase in KNOWSUB (1.44) yields a 0.24 increase in INTEREST (about one-fourth of a standard deviation of INTEREST).[12]

To explore the effect of college experience on the course choice decision further, we re-estimated the equations in Table 2, interacting three sources of information with years of college experience. In our focus groups, we found some evidence that upperclass students were more sophisticated in their use of information given by peers. Therefore, we interacted the importance of advice from peers who had taken the class and the importance of advice from peers who had not taken the class with college experience in both the PROFREP and INTEREST equations. We also interacted the importance of the advisor with college experience to determine if students become more refined in their use of information provided by an academic advisor.

The results of these estimations appear in Table 3. Results for the remaining coefficients are qualitatively unchanged from those discussed earlier, so we focus

Table 3: 3SLS results with experince interactions

	MATCH	**PROFREP**	**INTEREST**
PROFREP	.141** (3.41)		
INTEREST	.592** (7.33)		
Information Sources			
PEERSYES		.192** (3.26)	–.017 (0.36)
PEERSYES*COLLEXP		–.017 (0.73)	–.001 (0.07)
PEERSNO		.215** (2.19)	–.064 (0.82)
PEERSNO*COLLEXP		–.071* (1.89)	–.017 (0.56)
RA		–.165** (2.04)	–.023 (0.34)
ADVISOR		.165** (3.17)	–.099** (2.32)
ADVISOR*COLLEXP		–.059** (2.62)	.044** (2.42)
FACULTY		.009 (0.24)	.013 (0.41)
KNOWPROF		.401** (11.62)	
PROFDISC		.104** (2.50)	.055* (1.75)
SYLLABUS	.016 (0.44)	.029 (1.03)	
FIRSTWEEK	.075** (3.00)	.068** (2.12)	.011 (0.43)
HSTEACH			.003 (0.06)
HSEXP			.077** (2.74)
KNOWSUB			.151** (6.25)
CATALOG			.0.146** (5.92)
FAMILY			.048 (1.44)
Student/Course Characteristics			
DISTREQ	–.019 (0.83)		–.122** (5.35)
MAJREQ		.003 (0.16)	
DIVERSIFY	–.014 (0.60)		
FRIEND	–.030 (0.92)		
TIME	.007 (0.28)		
SCHEDULE	–.076** (2.49)		
WORKLOAD	–.064 (2.42)		
NOSTUDENTS	–.006** (2.70)		
COLLEXP	–.064** (2.37)	.334** (3.87)	–.036 (0.53)
INSTRGENDER		–.252** (3.23)	
INSTREXP		.011** (2.76)	
CLASSAVG	3.634** (2.75)	–1.663 (1.08)	
LEVEL		.002** (3.85)	
TIMFORGRADE		.155** (4.51)	
JOB			.128** (4.73)
R^2	.23	.39	.21
Number of Observations	839	839	839

**Significant at the 5% level; *significant at the 10% level. Absolute values of z-statistics are to the right of the coefficient in parentheses. All equations include a constant.

our discussion on the interaction terms. Interestingly, in the PROFREP equation, the coefficient on the interaction between importance of advice from peers who had not taken the class and college experience is negative and significant, suggesting that the use of information changes as students mature. Considering information provided by students who have not taken a specific class to be of lower quality than information provided by students who have actually taken the class, what we see is that as students progress through college, they are less likely to rely on this inferior information. While the results in column 2 of Table 3 still provide evidence of social learning, they also suggest that students become more sophisticated with experience. The coefficient on the interaction of importance of advisor and college experience in the PROFREP equation supports a conclusion that students change the process by which they make decisions as they progress through college. Students with less college experience rely more on their advisor for information about specific professors. One could also reasonably argue that this represents increased sophistication on the part of the students as they gain experience because academic advisors have, at best, only indirect knowledge of a specific professor's teaching qualities.

The results for the estimation of INTEREST with interaction terms also support these conclusions. Although the interaction terms with both variables relating to advice from peers are not statistically significant, the coefficient on the interaction between importance of advisor and college experience is positive and significant in the INTEREST equation. Notably, the positive coefficient on the interaction term is about half the size of the negative coefficient on importance of advisor, indicating that after about two years, students who are in classes because of their interests are also more likely to rely on the advice of their advisor. Because students receive advisors in their declared concentration at about this time, it is much more likely that students have an advisor whose expertise is more in line with their interests. Thus, this significant interaction term is likely to result from the combination of two effects: 1) students use the information from their advisor more efficiently as they gain experience, and 2) students are given access to better information as they progress through college.

Overall, our results indicate that the course choice process evolves as students gain more experience with it. Some peer networks become less important as students begin to rely more on their own experiences. The descriptive statistics presented in Table 1 suggest that older students are more likely to have had previous experience with the professor and the subject. Combined with the estimation results in Table 3, this indicates that students substitute their own experience for that of their peers as they solve the course choice problem again. This result is consistent with a social learning model in which individuals rely on social learning when the problem is

new and difficult to understand. As students gain more experience, they need to rely less on social learning because the problem becomes easier to solve and they are able to rely more on their own personal assessment.[13]

Conclusion

Students learn about making good course choices as they progress through college. This learning process exhibits both social and non-social characteristics. Interestingly, we find some evidence that college experience makes students more sophisticated in the way in which they learn from peers. We find little evidence that this process converges to herd behaviour, perhaps because the reliance on social learning decreases as experience increases.

The decision-making process that we have documented is indeed a complex one. One of the more important findings from an educator's standpoint is that students choose classes with very imperfect information about themselves and about the course. Instructors who want to ensure good 'matches' between their students and their class may want to proactively provide information to students about teaching methods, the topics covered and the assignments; the Internet may make this option viable for many instructors. For advisors of undergraduates, our results may also prove useful as our study documents that academic advisors may be underutilised and suggests the types of information that students deem important in selecting courses. Finally, for college administrators, our study shows that students may be somewhat unsystematically selecting classes; more support for assisting with this decision may result in students selecting classes for which they are better suited.

Overall, we do find evidence that students learn about making good choices as they progress through college, but the learning effects we find are very small. Perhaps our most interesting and hopeful finding is that the process of social learning adapts as students gain more college experience.

Appendix

Table A: Differences in proportions by college experience

	Third and Fourth Year Students Proportion – First and Second Year Students Proportion				
	Strongly Disagree	**Disagree**	**Neither Agree nor Disagree**	**Agree**	**Strongly Agree**
MATCH			–.05		.10
PROFREP	–.14	–.05		.06	.13
INTEREST			–.05		.06
PEERSYES					
PEERSNO					
RA	.07	–.04	–.03		
ADVISOR	.16	–.05	–.06		
FACULTY					
KNOWPROF	–.22		.03	.08	.13
PROFDISC	–.08		.04		
SYLLABUS		–.04		.046	.03
FIRSTWEEK	.08				
HSTEACH	.09		–.04	–.02	
HSEXP	.26	–.05	–.09	–.09	–.02
KNOWSUB	–.17			.06	.08
CATALOGUE	.07				
FAMILY	.14	–.06		–.05	
DISTREQ	.06	–.04	–.06		
MAJREQ					
DIVERSIFY	.06		–.06	–.05	
FRIEND	–.11			.05	.04
TIME	.07	–.11		–.04	
SCHEDULE				–.03	
WORKLOAD			–.09		
TIMFORGRADE				.05	
JOB	.08		–.05		

Only differences that are significant at the 10% level or better are reported. Blank cells indicate the difference was not statistically significant.

Table B: 2SLS results

	(1) MATCH	**(2) PROFREP**	**(3) INTEREST**
INTEREST	0.621 (7.25)**		
PROFREP	0.109 (2.48)**		
Information Sources			
PEERSYES		0.168 (5.22)**	−0.017 (0.66)
PEERSNO		0.055 (1.07)	−0.091 (2.14)**
RA		−0.124 (1.52)	−0.054 (0.76)
ADVISOR		0.046 (1.39)	−0.030 (1.08)
FACULTY		0.007 (0.19)	0.015 (0.45)
KNOWPROF		0.396 (11.14)**	
PROFDISC		0.105 (2.47)**	0.069 (2.08)**
SYLLABUS		0.017 (0.48)	0.026 (0.86)
FIRSTWEEK	0.073 (2.88)**	0.066 (2.03)**	0.013 (0.49)
HSTEACH			0.029 (0.51)
HSEXP			0.064 (2.13)**
KNOWSUB			0.152 (5.96)**
CATALOGUE			0.147 (5.65)**
FAMILY			0.042 (1.21)
Student/Course Characteristics			
DISTREQ	−0.023 (0.98)		−0.125 (5.30)**
MAJREQ			0.016 (0.71)
DIVERSIFY	−0.037 (1.50)		
FRIEND	−0.011 (0.32)		
TIME	0.005 (0.18)		
SCHEDULE	−0.041 (1.28)		
WORKLOAD	−0.049 (1.76)*		
NOSTUDENTS	−0.005 (2.06)**		
COLLEXP	−0.063 (2.29)**	0.063 (1.62)	0.027 (0.93)
INSTRGENDER		−0.268 (3.34)**	
INSTREXP		0.010 (2.46)**	
CLASSAVG	4.953 (3.55)**	−2.479 (1.56)	
LEVEL		0.003 (4.38)**	
TIMFORGRADE		0.151 (4.28)**	
JOB			0.124 (4.34)**
R-SQUARED	0.23	0.39	0.21
OBSERVATIONS	839	839	839

Absolute value of t-statistics in parentheses.

* Significant at 5%; ** significant at 1%.

All equations include a constant.

Table C: OLS results

	MATCH	PROFREP	INTEREST
PROFREP	.106** (5.05)		
INTEREST	.371** (12.66)		
Information Sources			
PEERSYES		.163** (5.10)	–.004 (0.17)
PEERSNO		.064 (1.25)	–.107** (2.64)
RA		–.131 (1.61)	–.058 (0.88)
ADVISOR		.046 (1.40)	–.029 (1.12)
FACULTY		.009 (0.24)	.010 (0.32)
KNOWPROF			0.390** (11.01)
PROFDISC		.099** (2.35)	.072** (2.32)
SYLLABUS		.014 (0.39)	.013 (0.464)
FIRSTWEEK	0.100** (4.48)	.063** (1.96)	.022 (0.84)
HSTEACH			.034 (0.62)
HSEXP			.067** (2.33)
KNOWSUB			.142** (5.80)
CATALOGUE			.139** (5.58)
FAMILY			.027 (0.81)
Student/Course Characteristics			
DISTREQ	–.038* (1.85)		–.132** (5.80)
MAJREQ			.012 (.056)
DIVERSIFY	–.006 (0.29)		
FRIEND	–.012 (0.42)		
TIME	.011 (0.42)		
SCHEDULE	–.077** (2.75)		
WORKLOAD	–023 (0.93)		
NOSTUDENTS	–0.008** (3.88)		
COLLEXP	–0.19 (0.85)		
INSTRGENDER		–.273** (3.44)	
INSTREXP		.011** (2.77)	
CLASSAVG	3.615** (3.15)	–2.618* (1.68)	
LEVEL		.003** (4.66)	
TIMFORGRADE		.156** (4.46)	
JOB			.120** (4.42)
R2	.29	.38	.19
Number of Observations	895	862	916

**Significant at the 5% level; *significant at the 10% level.

Absolute values of t-statistics are to the right of the coefficient in parentheses.

All equations include a constant.

Notes

1 For studies of the choice of major and its impact on occupational choice, see Gill and Leigh (2000), Turner and Bowen (1999), Eide and Waehrer (1998), or Loury (1997). Others have focused specifically on the choice of the economics major. See, for example, Jensen and Owen (2001) or Fournier and Sass (2000). Dynan and Rouse (1997) focus on the choice to major in economics, but also investigate the choice to take the first economics class.

2 For surveys, see Gale (1996) and Bikhchandani *et al*. (1998). See also Allen and Carroll (2001), Moffitt (2001), Duflo and Saez (2003) or Çelen and Kariv (2004).

3 The survey instrument is available upon request. It contains a question asking students if they have filled out the survey in a previous class. Students who answered yes to this question or who were unsure are dropped from our sample.

4 It is extremely uncommon at this institution for students to drop a class without adding another.

5 We also experimented with using students' expected relative grade (expected grade/GPA) as the dependent variable; however, we concluded that this measure is not a good measure of optimal course choice because it is too narrow, capturing mostly the lack of rigour in the course. For example, interest in the subject is negatively associated with relative grade, but the importance of the expected workload in the class is positively associated.

6 Results presented later show that the expected importance of the course for the students' future career is related to interest in the subject, suggesting that students are indirectly taking into account future economic opportunities that result from the course when assessing the quality of the match.

7 See, for example Falchikov and Boud (1995) or Nowell and Alston (2007).

8 It is possible that the high school experience was influenced by social learning; however, our data does not allow us to explore this hypothesis. Nonetheless, once students are in college, the fact that the previous experience has an impact is inconsistent with a social learning process continuing in college.

9 CLASSAVG is the average of each student's expected grade/GPA, i.e. the average of RELGRADE for a given course. Higher values of CLASSAVG indicate that, on average, students expect to earn better grades in this course than in others they have taken.

10 The p-value for the second Hausman test was 0.45, which does not allow us to reject the null hypothesis that differences in the coefficients from the two estimations are not systematic. We also performed a Sargan test for overidentifying restrictions and do not reject the null hypothesis that our instruments in our 3SLS estimation are valid, with a p-value of 0.3.

11 The reader will note that in performing the estimations reported in Table 2, we lose observations because we do not have data for all the variables for all observations. An examination of the number of observations for each variable that are reported in Tables 1A, 1B and 1C, however, reveals that there is no pattern to the missing variables - missing observations are not due to missing data for any one specific variable. Because of this, we do not believe that the results are biased by the missing observations.

12 Half of the students in our sample is female. Interestingly, when we explore if there are differences between male and female student behaviour by interacting PEERSYES, PEERSNO, PROFREP and INTEREST with a gender dummy, we do not find

any statistically significant interactions. While it is possible that male and female students choose and evaluate courses differently, we find no evidence of it in our data.

13 One might want to calculate the marginal effect of college experience in the estimations reported in Table 4. If one considers only the direct effects by accumulating the marginal effects for each coefficient that involves COLLEXP, the average of the marginal effects is negligible (-0.01). However, this method underestimates the actual effect of additional experience because some of the independent variables in the estimation are correlated with experience (notably KNOWSUB and KNOWPROF).

References

Allen, Todd W. and Christopher D. Carroll (2001) 'Individual Learning About Consumption' *Macroeconomic Dynamics*, 5(2): 255–71.

Arcidiacono, Peter and Sean Nicholson (2005) 'Peer effects in medical school' *Journal of Public Economics*, 89: 327–50.

Banerjee, Abhijit (1992) 'A Simple Model of Herd Behavior' *Quarterly Journal of Economics* 107, 797–817.

Bikhchandani, Sushil, David Hirshleifer and Ivo Welch (1998) 'Learning from the Behavior of Others: Conformity, Fads, and Informational Cascades' *Journal of Economic Perspectives*, 12(3): 151–70.

Çelen, Bogaçhan and Shachar Kariv (2004) 'Distinguishing Informational Cascades from Herd Behavior in the Laboratory' *The American Economic Review*, 94(3): 484–98.

Duflo, Esther and Emmanuel Saez (2003) 'The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment' *Quarterly Journal of Economics*, 118(3): 815–42.

Dynan, Karen E. and Cecelia E. Rouse (1997) 'The Underrepresentation of Women in Economics: A Study of Undergraduate Economics Students' *Journal of Economic Education*, 28(4): 350–368.

Eide, Eric and Geetha Waehrer (1998) 'The Role of the Option Value of College Attendance in College Major Choice' *Economics of Education Review*, 17(1): 73–82.

Falchikov, Nancy and David Boud (1989) 'Student Self-Assessment in Higher Education: A Meta-Analysis' *Review of Educational Research*, 59(4): 395–430.

Fournier, G.M. and T.R. Sass (2000) 'Take My Course, Please: The Effects of the Principles Experience on Student Curriculum Choice' *Journal of Economic Education*, 31(4): 323–39.

Gale, Douglas (1996) 'What Have We Learned from Social Learning?' *European Economic Review*, 40(3–5): 617–28.

Gill, Andrew M. and Duane E. Leigh (2000) 'Community College Enrollment, College Major, and the Gender Wage Gap' *Industrial and Labor Relations Review*, 54(1): 163–81.

Jensen, Elizabeth J. and Ann L. Owen (2001) 'Pedagogy, Gender, and Interest in Economics' *Journal of Economic Education*, 32(4), 323–43.

Light, Richard J. (2001), *Making the Most of College: Students Speak Their Minds* (Cambridge: Harvard University Press).

Loury, Linda D. (1997) 'The Gender Earnings Gap Among College-Educated Workers' *Industrial and Labor Relations Review*, 50(4): 580–93.

Moffitt, Robert A. (2001) 'Policy Interventions, Low-Level Equilibria, and Social Interactions' in *Social Dynamics*, ed. by Steven N. Durlauf and Peyton Young (Cambridge: MIT Press).

Nowell, Clifford and Richard M. Alston (2007) 'I Thought I Got an A! Overconfidence Across the Economics Curriculum' *Journal of Economic Education*, Spring: 131–42.

Pascarella, Ernest T. and Patrick T. Terenzini (1991) *How College Affects Students* (San Francisco: Jossey-Bass Publishers).

Sabot, Richard and John Wakeman-Linn, 1991, 'Grade Inflation and Course Choice', *Journal of Economic Perspectives* 5(1): 159–70.

Sacerdote, Bruce (2001) 'Peer Effects with Random Assginment: Results for Dartmouth Roommates' *Quarterly Journal of Economics*, 116(2): 681–704.

Schuhmann, Peter and KimMarie McGoldrick (1999) 'A Conjoint Analysis of Student Registration Decision Making' *Journal of Excellence in College Teaching*, 10(3): 93–121.

Turner, Sarah E. And William G. Bowen (1999) 'Choice of Major: The Changing (Unchanging) Gender Gap' *Industrial and Labor Relations Review*, 52(2): 289–313.

Winston, Gordon and David Zimmerman (2003) 'Peer Effects in Higher Education' The Williams Project on the Economics of Higher Education Working Paper #DP-64.

Zimmerman, David (1999) 'Peer Effects in Academic Outcomes: Evidence from a Natural Experiment' The Williams Project on the Economics of Higher Education Working Paper #DP-52.

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