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ABSTRACT

Tracking the Herd with a Shotgun — Why Do Peers Influence College Major Selection?*

How do peers influence people's choices? We explore this fundamental question by exploiting unique data produced by, and a natural experiment conducted on, students from the United States Naval Academy (USNA). We develop a conceptual framework to highlight that individuals can emulate others for both information (social learning) and for socializing (network externalities). We then analyze data on the preliminary preferences and ultimate major selections of USNA freshmen, exploiting a rich set of covariates and the random assignment of students to peer groups. We find that students can be influenced by peers into selecting different academic paths relative to what they would have chosen on their own. Through random reassignments of certain student groups into new peer groups, we also explore the reasons why herding occurs. The preponderance of evidence suggests that social learning, as opposed to network externalities, is the key driver for herding behavior.

JEL Classification: D85, I21, I23, J24

Keywords: major selection, peer effects, higher education, herding, social networks

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1 Introduction

How important are your peers when making important decisions in life? When choosing where to live, or what car to purchase, or what career to pursue, it is rare for us not to be influenced by what others have chosen to do in the past. How powerful these influences are, and whether or not such influences result in better decisions, remain critical areas of inquiry.

Furthermore, *why* do people emulate others? There are two big motivators. One is "social learning" — people derive information regarding their own choice set from other people's choices (Banerjee, 1992; Moretti, 2008). The other is "network externalities" — people may derive utility simply from doing what others do. These two factors can often conflict with each other. For example, as stressed in Moretti (2008), people can infer the quality of a movie by how many people are queued up to watch it. On the other hand, people may be willing to watch a bad movie if there are others also watching to collectively mock it (who after all would want to watch a bad movie alone?). In some situations some may even prefer to watch a bad movie with others than to watch a good movie by themselves.

Disentangling these two motivations to "herd" — that is, to follow what others choose to do even if they have prior information suggesting a better alternative — is a difficult challenge. The mechanisms at work matter crucially for policy makers who wish for people to make "correct" decisions in the face of uncertainty. For example the effectiveness of greater knowledge dissemination to people will depend, among other things, on the responsiveness of people to such knowledge, and on the importance of the social benefits of making any choice that others have chosen.

This paper documents and analyzes the relative importance of each of these factors in the context of academic major selections in college. Peer effects in college major selection have been studied in other works such as Sacerdote (2001) and De Giorgi et al. (2010). The former study does not find any peer influence but cannot separate exogenous from endogenous effects. The latter employs an identification strategy on business students at Bocconi University and finds students are more likely to choose a major when many peers make the same choice. These works however cannot distinguish between social interaction effects and information effects. This would seem to be the next natural area of exploration.

We first discuss a conceptual framework where the effect of more accurate information on herding behavior is ambiguous, depending on the past choices of individuals and the importance of network externalities. To explore these ideas further we turn to students at the United States Naval Academy (USNA) choosing from among a discrete set of majors.

USNA is an elite 4-year liberal arts college with a curriculum typical of such institutions. It does however have a number of unique features making it an ideal setting for the questions we pose. First, freshman are randomly assigned dormitories, and all students must live on campus for their full four years. This makes for very stable and influential peer group formation. While this is also true of all service academies, USNA has two other features that uniquely help us unpack potential mechanisms, one related to the importance of information in making decisions, the other related to the importance of social groups in making decisions.

First, all freshman must take a standard set of courses with no discretion over instructors or timing, and must choose an academic major early in their second semester. Because only a subset of major subjects are sampled before one is compelled to pick a major, there is asymmetric information over subject matter across subjects. Further, the timing of two courses among the set of freshman offerings is randomized, with half the class taking one type and the other half taking the other type during the fall semester, then with students swapping courses during the spring semester. This allows us to gauge the importance of information gleaned from content sampling and grade signals in the choice of major in a way not possible in other colleges.

Second, there were periods when dormitories at the Academy were "shot-gunned." This meant reassigning students to a new dormitory after their freshman year. It effectively broke up the social network, an important source of camaraderie and information for students. This uniquely allows us to explore what happens to peer influence when social networks are randomly disrupted.

Along these lines, we can also observe which sub-peer-group appears to motivate major selection. We can also observe if homophily plays a role (for example, do women emulate other women, or minorities other minorities?). In the end, we are, to our knowledge, the first work to disentangle these two channels for herding when both have the potential to exist.[1]

Preview of Empirical Findings

Our findings offer a number of insights. First, students often appear to copy their upper-classmates in choosing an academic major. The majority of majors exhibit a higher likelihood of joining if there are greater numbers of prior generations of students having joined. This is a unique finding from most studies on the peer influences of major selection, which mainly focus on contemporaneous peers. Our study instead observes the sequential nature of major selection, leading to herding behavior as discussed in Banerjee (1992).

Second, those who herd tend to perform slightly better in follow-on coursework, after controlling for a wide variety of observable characteristics. This gives suggestive evidence that herders are not substituting grade performance for social belonging. Rather they may be gathering information from their peers to make better decisions.

This leads us to our third finding — grade signals appear to help students veer away from herding. Thus

[1] Most scenarios involve either strictly social learning (such as learning from others about the quality of movies or restaurants [see for example Moretti, 2008]) or strictly network externalities (such as joining a fashion trend [Karni and Schmeidler, 1990] or working with more productive people [Katz and Shapiro, 1985].

when students use upper-classmates to inform them about majors, direct experience with the courses can lead them to substitute away from peer signals. This would again suggest that social learning may be an important motivation for why people herd, especially when personal information is lacking.

Fourth, students do not fundamentally change their behavior during times when the social group stabilizes (i.e. when shot-guns cease). This is evidence pointing again to the idea that social learning is the key channel — students tend not to respond when the social benefits of herding, relative to the academic benefits, rise.

Fifth, homophily does not appear to play an important role in herding. For example, female students do not appear to herd towards other females. This is true even for science, technology, engineering, or math (STEM) focused majors — in fact, female students tend to respond to their own grade in freshman STEM courses more than their male counterparts. This implicitly challenges the notion that female role models in technical fields are important drivers for later generation of women joining such fields (Carrell et al., 2010). It may also further suggest the importance of social learning, rather than factors related to social belonging.

Finally, we observe an interesting exception to the above for one major — math. For math majors the social network appears to matter — positive grade signals do not dampen the herd effect, and this effect strengthens when the social network stabilizes. This makes sense, as math is a kind of "gateway" subject. Doing well in math means potentially doing well in a host of engineering and other STEM fields. With many other comparable choices, students may also need a robust social network to be enticed to be a full-fledged math major.[2]

The rest of the paper proceeds as follows. Section 2 briefly discusses some related literature. Section 6 develops the basic theory, produces some testable implications, and connects the theory with our unique empirical setting. Section 4 describes the data. Section 5 provides the empirical analysis and results, and suggests some of the policy implications from herding behavior. Section 6 provides concluding comments.

2 Related Literature

The extent, and reasons why, individuals emulate others remains a robust area of economic research. One reason has to do with information — some may believe that others are better informed than themselves, and follow them, potentially disregarding their own information. This has been documented in financial markets (Devenow and Welch 1996), as well as other diverse areas of decision making in politics, science and popular culture (Bikhchandi et al. 1992). The extent of these so-called "information cascades" (Bikhchandi et al. 1992) can be affected by many factors related to fear (Economou et al. 2018), uncertainty (Lin 2018), or a shared identity of decision makers (Berger et al. 2018).

[2]One might consider a sports parallel. When one discovers she is a fast runner, she may join Track and Field (as opposed to soccer or field hockey or something else) only if her friends join as well.

An alternative though not mutually exclusive reason to do what others do is because of the existence of network externalities. This is where "...the utility that a user derives from consumption of [a] good increases with the number of other agents consuming the good" (Katz and Shapiro 1985). Such consumption externalities have been documented in areas such as telecommunications, computer software, automobile repair, and even video games (Liebowitz and Margolis 1994). More recent work by Gilchrist and Sands (2016) focuses on the importance of network externalities on movie sales.

There are many cases where both social learning and network externalities are present in networks. Few works to date however are able to adequately disentangle the two effects. Fafchamps et al. (2016) distinguish between the two in a study of the adoption of airtime transfers. Huang et al. (2017) attempt to identify these effects in consumers' choice of films. No study to our knowledge makes this distinction in college major choice, even though networks appear to play a vital role in the choice (Griffith and Main 2019).

Of course many studies have focused on *other* factors which affect major choice. For example Rask (2010) finds in a student sample from a liberal arts college that grades play a more important role for major selection among men, while preferences play a stronger role among women. Bordon and Fu (2015) focus on the potential of student-major mismatches, and explore the equilibrium effects of student choice of major.

Another line of inquiry attempts to understand the falling enrollment of students studying STEM fields. Stinebrickner and Stinebrickner (2014) studies why individuals choose STEM-oriented majors, given initial learning over individual abilities. Kinsler and Pavan (2015) on the other hand show that the uncertainty over future productivity at the time of major selection makes STEM oriented majors less appealing.

How important are future earnings in major choice? Montmarquette et al. (2002) is one of the first papers to study the choice of major by college students, suggesting that expected future earnings play the most important role in this choice. Wiswall and Zafar (2015) demonstrate how individuals update their beliefs concerning majors. Importantly for our study, they show that while expected earnings and perceived ability are significant factors in major choice, heterogeneous preferences appear to be the dominant factor. The importance of non-pecuniary factors is echoed in Arcidiacono (2003), Beffy et al. (2011) and Altonji et al. (2015).

Yet another line of inquiry studies how the composition of faculty teaching entry-level courses (Griffith, 2014) or the gender and ability composition of classmates (Feld and Zölitz, 2018) may sway students to pick certain majors. This can be important for female enrollment and completion of STEM degrees (Carrell et al., 2010); the gender gap in the probability of completing a STEM degree has been estimated to be between 50 and 70 percent (Weinberger, 2001).

Finally, using data from a similar college setting, Patterson et al. (2019) investigate the major selection process at the United States Military Academy (USMA). They demonstrate that the order of exposure to certain subjects affects students' major choice.

In this study we investigate the mechanisms through which peers can influence the choice of undergraduate major. They may do so for two broad reasons — they may facilitate social learning under uncertainty (a student has no idea what they should major in so they assume older classmates know more) and/or they may generate a potential network externality (by choosing a particular major a student identifies with a particular social network). While De Giorgi et al. (2010) find peers impact major choice which in turn impacts earnings, they are unable to isolate why. This paper takes a step forward in identifying the mechanism by observing major choice when students are able to substitute pseudo peer signals for own grade signals, both with and without socially stable peer groups.

3 Conceptual Framework

A stylized model where heterogeneous agents sequentially choose from among two options is presented in the appendix. Much like freshmen in college, agents in the model are uncertain both about their own type (for example, if they are a "math-type" or a "languages-type") and about which choice would be appropriate for each type (for example, how much math and language content there is in each choice). Agents have imperfect information regarding these facts, but can observe the choices made by prior generations of agents.

The key takeaways from the framework are straight-forward. We can observe how the decision of any individual agent may be shaped by 1) the choices of prior agents, and 2) the accuracy of information. First, for a given quality-level of information regarding choices, more prior agents choosing one option will raise the likelihood that the agent will herd (i.e., choose the more popular option). Second, for a given distribution of prior peers having made their choices, better information regarding these choices for everyone will lower the likelihood that the agent will herd. The first result has been established by Banerjee (1992). The second is new, at least to our knowledge. On the one hand, better knowledge means that prior peers are making more informed decisions, hence the "herd signal" is more valuable. On the other hand, the herd signal remains noisy compared to your own, since peers might not be the same type as you, or they might have guessed. We suggest that under most plausible scenarios, the latter factor dominates the former.

Finally, we also see that in the presence of stronger network externalities, better information regarding choices may not change herding behavior as much. This makes sense since in this case finding the "right match" may not be as important as simply joining the more popular choice.

4 Setting

To test the ideas of this framework, we use the case of students at USNA choosing their college major. As we hope to make clear below, this is an ideal social environment to explore the ideas of the theory, both because of the structure of the institution and the random shocks imposed on the students.

4.1 Data and External Validity

USNA is both a service academy and a liberal arts college. We exploit the educational structure and ideal experimental design imposed by the former while still gaining the external validity provided by the latter. Graduates earn a Bachelor of Science degree in one of approximately 25 majors. In this respect USNA is similar to USMA and USAFA (see, for examples, Lyle [2007, 2009] and Carrell et al. [2009] respectively). However, USNA's academic setting is distinct from USMA and USAFA in that the Naval Academy's faculty is at least fifty percent tenure-track civilian, career academics (this statistic tends to be as high as 60 percent in practice due to unfilled "billets" on the military side; see Keller et al. [2013]). In contrast, USMA's faculty model targets 25 percent civilian, while USAFA targets 29 percent (Keller et al., 2013). The civilian tenure-track faculty are required to have earned a Ph.D and are evaluated for tenure according to guidelines that are similar to "regular" colleges and universities. The military faculty predominantly hold Masters Degrees (a small percentage have Ph.Ds).

For these reasons USNA is academically comparable to other schools studied in the peer effects literature (see, for examples, Zimmerman [2003] and Stinebrickner and Stinebrickner [2006]). In addition, USNA's student body is representative of the pool of graduating high school seniors applying to competitive institutions (for further discussion see Brady et al. [2017]). All students undertake a "core" academic curriculum, which consists of a broad range of subjects taught by subject matter experts, as well as a standard college major. The number of students per section in any given course rarely exceeds 25, and student interaction with faculty members in and outside of the classroom is similar to a liberal arts college setting. There are a variety of academic majors offered at USNA across the humanities, social sciences, natural sciences, and engineering. Due to these and other factors, the Naval Academy is consistently characterized as a top 20 liberal arts college by U.S. News and World Report.

4.2 Dataset

Our dataset allows us to analyze the major choices of over 23,000 USNA students who were freshmen during academic years 1996 through 2015. Administratively collected data for each student's high school characteristics and their achievement while at USNA were provided by the Office of Institutional Research.

Student-level summary statistics are provided in Table 1. Students at USNA are relatively high achievers, with average math and verbal SAT scores at the 88th and 82nd percentiles of the nationwide SAT distribution.[3] Students are selected from each congressional district in the U.S. by a highly competitive process, ensuring geographic diversity. Nine percent of total applicants were admitted to USNA in 2017.[4] For our data, approximately 20 percent of the students are female, six percent are Black, 10 percent are Hispanic and four percent are Asian.

Students also can originate from one of three possible feeder sources: they can be admitted directly, they can be assigned to a one-year pre-college preparatory program called the Naval Academy Preparatory School (NAPS) before admittance, or they can be assigned to a one year private pre-college program of the student's choosing through the Academy's Foundation program. Approximately 23 percent of all incoming students in our data first attend a pre-college program (Kotlikoff et al., 2021). Seven percent of students were previously enlisted in the armed forces.

Finally we observe students' major, grade from every course they take, and various military achievement metrics that are assigned semester-by-semester.

4.3 Student Assignment to Companies and Courses

Upon arrival, every freshman is assigned to a company. All students live in one on-campus dormitory, which houses 30 companies of approximately 150 students, each containing an even mix of freshmen, sophomores, juniors, and seniors. A student's company makes up his or her basic group of potential peers. The company assignment procedure, which is administered by the Admissions Office, is designed to produce a demographically diverse but otherwise randomly allocated mix of students in each company. Students are first stratified according to certain predetermined characteristics: race, gender, home state, prior military service, and attendance at NAPS. Once administrators ensure balanced representation among these characteristics across all companies, they randomly assign all remaining students to companies. The key features of the procedure are that students have no control over the outcome—USNA does not solicit interests, lifestyle details, or roommate preferences as is typical of other universities—and it produces an allocation that is effectively random. Importantly for our study of major choice, freshmen have no control over who their upperclass companymates will be, and so the distribution of majors among upperclass companymates is exogenous to each freshman.

Brady et al. (2017) presents standard resampling tests for the same set of students, and demonstrates that assignment of freshmen to companies is effectively random. We may also test this exogeneity assumption in

[3]Provided by "SAT: Understanding Scores" — The College Board 2017.
[4]Based on authors' calculations.

the following manner, which is more tailored to the current application. For each of the 18 majors displayed in Table 2, and for each academic year, we carry out three regressions: Using the sample of freshmen from the given academic year, we regress the proportion of senior companymates in a given major on freshmen's pretreatment background characteristics (all variables listed in Table 1 except for academic and military GPA). We then perform the same regression using the proportion of junior companymates in a given major as the dependent variable, and then finally using the proportion of sophomore companymates. These three regressions across 20 academic years and 18 majors comprise a set of 1,080 regressions.[5] If the distribution of upper-classmates' majors within companies is exogenous for a given matriculating freshman class, then freshmen's observable characteristics should be unrelated to these dependent variables. Thus the collection of F-statistics from this series of regressions should form an F-distribution that is predominantly beneath a standard threshold of statistical significance. Figure 1 shows the histogram of F-statistics. The vertical line indicates the critical value for an $F(12, \infty)$ distribution at a 10 percent level of significance. The vast majority of F-statistics generated from the series of regressions are less than the critical value, indicating that observable pretreatment characteristics are not correlated with the major choices of a freshman's upperclass companymates.

Freshmen have more or less no direct choice over the courses they take. All freshmen must pass or validate a set of 11 core courses in a range of subject areas. Approximately half of the freshman class will take five classes in the fall, and the other half will take six (then six and five, respectively, in the spring).[6] Students cannot choose whether they take five courses or six that first semester, or if they take U.S. Government or American Naval History during the fall semester (these outcomes are a function of company assignment; both courses are freshman-year requirements but cannot be taken during the same semester). It is possible for students to validate freshman year courses through USNA-administered placement exams or advanced placement scores (e.g., a student that validates Calculus I via AP scores will take Calculus II during the fall semester). The validation exams are the only form of indirect student input in the process.

Once students near completion of their freshman-year courses, they are required to select a major. This process is described in detail in section 4.4 below. Students then take a combination of core and major-specific courses through the rest of their college years. Core courses involve topics deemed important for every officer in naval service to understand, such as thermodynamics, electrical engineering, and leadership. Major

[5] In actuality we run 1,016 regressions because some majors were created during the sampled years (Quantitative Economics, Arabic, and Chinese) or removed from the academic program (Information Technology).

[6] A freshman with six courses in the fall will take Calculus I, Chemistry I, English I, and then either U.S. Government or American Naval History, and Seamanship, and a course called Prepare to Lead. A student with five courses in the fall will also take Calculus, Chemistry, English, and then either U.S. Government or American Naval History, but instead of the Seamanship and the leadership course, they will take Cyber Science. Over the years of our sample, the core freshman-year *professional* (i.e., non-academic) courses (currently Seamanship and Preparing to Lead) has changed several times. In academic year 2012, a previously offered professional course, Introduction to Navigation, was eliminated to free up space for the new Cyber Science course. For these reasons, this paper's analysis excludes professional courses and the Cyber Science course in the relevant places.

specific courses on the other hand are those applicable to the major subject and comparable to major-specific curricula established by typical colleges and universities. Such comparability is ensured by the Middle States Association of Colleges and Schools and the Middle States Commission on Higher Education, who evaluate each major periodically in order to assess and advise faculty over potential curricular changes and updates.

Finally, all graduates of USNA have a five-year commitment of military service, either in the U.S. Navy or the U.S. Marine Corps. After this obligatory service many opt to exit the naval service and leverage both their education and military experience in the civilian labor force. Thus the long-run private return of a college major at USNA can be considered comparable to any other university, only with a more lagged term structure.

4.3.1 The Shot-gun

The classes of 1996 through 2006 were nearly always "shot-gunned." This involved randomly reassigning students to new companies following completion of their freshman year. There are two varieties of shot-gunning: either the entire freshman class of one company was reassigned to a different company (keeping the freshman cohort together, which is the "standard shot-gun"), or every freshman was randomly reassigned, irrespective of their company of origin (this is called "the blast.").

The purported reasons for shot-gunning freshmen in this manner were numerous, and depended on the Commandant in charge of executing the shot-gun: it breaks up freshman-year cliques; it forces readjustment and builds character; it makes those who did well as freshmen not rely on that reputation, thus preventing complacency; it lets those who perhaps did not do well freshman year to get a fresh start; it's a chance to learn how to deal with new leadership. Whatever the motivations, they had nothing to do with major selection and composition (it is unlikely the Commandant would even have access to the selection of majors by freshman). This provides us with a truly *sui generis* experiment at the college level that helps us answer one of our big questions: how important is a stable social network in facilitating herd behavior.

Prior to 2003 (when the last class of freshmen were shot-gunned), observed herding behavior can be attributed mainly to social learning. Any network externality effects from choosing a major would conceivably dissipate next academic year as one's social group among upperclassmates is completely reformed. After 2003 however, shot-guns ceased and social networks stabilized. During this period herding could involve both social learning and network externalities — changes in herding behavior might then be associated with relatively higher weight placed on the social network in forming major choices. We investigate this within the empirical exercises to come in section 5.

4.4 The Major Selection Process

One of the institutional features of USNA that facilitates our study is that all students must declare their college major during the middle of the second semester of their freshman year.[7] This provides us with an exceptionally clean experimental design not afforded to studies of other universities, where students can declare their majors at different times or "shop around" for subjects in various ways during different portions of their college careers. Before making their decision each USNA freshman will have two basic sets of information: a portfolio of grade signals from a set of first semester courses (as well as preliminary grade signals from a set of second semester courses), and a close-knit group of upper classmates with their prior major selections. Although obviously grade and peer signals will vary student to student, all will have access to these two different channels through which to make their decision.

In addition academic departments organize informational sessions for freshmen regarding subject material within each major periodically throughout their academic year, typically one or two evenings during the fall semester and once more during the early spring semester. Freshmen are required to attend such sessions for all majors in the fall; however in the spring they may target those few specific majors that they are considering. While these sessions can provide students at least a glimpse of all subjects, it remains the case that students learn much more about certain subjects during their freshman year than other subjects (for example, as discussed above, introductory-level chemistry and political science courses are required within the first two semesters), leading to information gaps and asymmetric information.

Other features at USNA also help our study. Double majors are extremely rare, and virtually impossible without considerable course validations from high school. Major switches by students after freshman year are also very rare because students have limited ability to change course yet still graduate in the (federally mandated and administratively enforced) four year window. Any such changes are almost always *within* each major, such as switching to or away from an honors track.

Table 2 provides summary statistics regarding the overall number of students in each major. Majors at the Academy have historically been grouped into one of three overall categories: engineering (group I), math/sciences (group II), and humanities/social sciences (group III).[8] Within STEM fields we see that the most popular group I majors are systems and mechanical engineering, while the most popular group II major is oceanography. The most popular group III majors are political science and economics. Despite the greater popularity of certain majors, there is a wide range of majors with a wide distribution of student enrollment for both technical and non-technical fields.

[7] Specifically, March of their freshman year, according to USNA Plebe Advising Handbook.

[8] This explicit categorization was eliminated in 2016 for reasons that remain obscure.

5 Statistical Methods

This section proposes a series of empirical exercises in order to test certain aspects of our theoretical framework. Extending the model outlined in section 6, we now have N choices (instead of just 2), with numerous individuals from prior generations having chosen among these. We also have "rewards" from one selection that may differ across individuals. Nonetheless peers can help signal to freshmen which may be the more rewarding choices, and may further reward major selectors through network externalities.

5.1 Modeling Major Selection

5.1.1 Does Herding Occur?

To help us answer this question we estimate a series of binary choice models, with the choice characterized either as the group (groups I, II or III), or as the individual major (those listed in Table 2).[9] For example, consider the following linear probability model of one's decision to major in economics versus some other major:

$$Pr\left(ECON_{ict}=1\right)=\alpha+X_i^{'}\beta+\delta\frac{\sum_k ECON_{kct}}{n_{ct}}+\eta_t+\epsilon_{ict}. \tag{1}$$

$ECON_{ict}$ is a binary indicator of whether student i in company c in graduating class t chose economics as his or her major. X_i includes pretreatment control variables such as gender, age, race/ethnicity, SAT scores, and other background characteristics. $(\sum_k ECON_{kct})/n_{ct}$ measures the proportion of upperclass company c mates (i.e., all k sophomores, juniors, and seniors within company c) during i's freshman year who majored in economics. Note that for every freshman, this term is exogenous because all of i's upperclass companymates chose whether or not to major in economics before i enrolled. η_t represents a set of binary controls for graduating class years, and ϵ_{ict} is an individual-specific error term. We estimate such a regression for each potential major.

Table 3 provides results from equation (1) when characterizing the choice as the group. These are estimated via OLS. We first note that we observe notable and statistically significant estimated effects for choosing group I majors (engineering). Estimates for group II and III majors are both smaller and statistically insignificant. There are two things to point out here. First, group I is the only group that has no representation in the freshmen core of courses. This constitutes our first piece of evidence that suggests that better information can potentially stem herding. Second, the wide heterogeneity of majors within

[9] We can also estimate multinomial choice versions of the major selection process (e.g., via a multinomial logit model). While we find similar trends in peer effects, results are harder to interpret given the non-linear model, so we prefer simple linear probability models for exposition. A full set of results is available upon request.

groups II and III may muddle our findings.

To address this we turn to Table 4, which provides results from equation (1) for each major estimated via OLS. The table displays results for those majors where estimates of the peer effect coefficient are statistically significant (seven out of 18 majors). Looking at such a large peer group (recall that each company contains approximately 150 students) whose group members may choose from among a large menu of options, measured peer effects may be somewhat attenuated. Still, we observe seven majors where this aggregate peer measure exhibits a statistically significant pull on student choice. For example, a ten point increase in the percentage of upperclass companymate history majors causes one's own chance of majoring in history to increase by two percentage points. Also note that all but one major in this list are STEM majors. This might again suggest that peer influence can help students choose technically-focused education. This is an insight not much discussed in existing literature. If anything, recent studies suggest that peer effects can *decrease* STEM education (see for example Fischer [2016] and Anelli et al. [2017]). Our findings here may help educators bent on bolstering STEM-oriented education find new peer-to-peer approaches to achieve this goal.

While not statistically significant, peer effects for other majors exhibit similar estimated magnitudes, and no majors exhibit statistically significant *negative* push-effects on student choice (see Figure 2 for the full set of point estimates and their confidence intervals for all majors).

To take another step in uncovering potential mechanisms, Table 5 presents results from a version of equation (1) where the peer effect has a different coefficient for each cohort of upperclassmates in company c (sophomores, juniors and seniors). To our knowledge no work on the peer influences of major choice have disaggregated the effects in this manner. We see that, out of 18 majors, 12 now exhibit net positive peer influence on student choice from at least one upperclass cohort. Eight majors exhibit statistically significant positive peer influence from sophomores, while six majors exhibit statistically significant positive peer influence from seniors. Only two majors have any such effects coming from juniors. This makes some sense; sophomores will be closest to freshman socially, potentially generating both social learning and network externalities. Seniors will have the most complete information regarding each major, but little value in social networks as none will be present next academic year (there are no fifth-year students given the four-year graduation window that is federally mandated).

Among these 12 majors, we observe a few negative estimates from peers, usually from juniors but statistically insignificant in all but one case. It thus appears at first pass that both social learning and network externalities may be present in the motivation to herd. The net estimated effects across all classes of peers for all majors are always positive if statistically significant (Table 4). Figure 3 displays point estimates and confidence intervals for all majors.

5.1.2 Robustness of Herding Effects

As part of the major selection process, freshmen are required in December to rank their top three choices of academic major.[10] This ranking does not in any way bind the student to any particular choice; it merely captures preliminary information that is useful for the Registrar's Office and for academic advising purposes. We can use these preliminary major preference rankings as a simple robustness check where we introduce an additional peer effect channel: How might a freshman's *freshmen* companymates contemporaneously affect her major choice decision?[11] We cannot claim causal identification of this contemporaneous herding effect because we cannot disentangle simultaneous effects (since freshmen choose majors concurrently), but a positive correlation between freshmen companymates' major choices alongside the positive upperclass companymate peer effects (uncovered in the previous tables) would bolster our finding that inter-generational herding behavior exists.

For this experiment, we aggregate preliminary major preference ranking data into a company-wide "score:" For a given major, five points are contributed if a freshman selected the major as her first choice, three points as her second choice, and two points as her third choice. The peer variable is then the company-wide aggregate score for a major divided by the number of freshmen within the company. We estimate equation (1) as before, now including this additional peer effect channel.

Table 6 contains results. Many of the majors that are already represented in Tables 4 and 5 (i.e., those where we found statistically significant inter-generational herding effects) exhibit *contemporaneous* herding effects alongside inter-generational effects. Three of the majors that do not produce a statistically significant effect of inter-generational herding do show contemporaneous herding (Aerospace Engineering,[12] Mechanical Engineering, and Oceanography), which suggests that the freshman-to-freshman peer effect coefficient might be picking up more than simultaneous effects.

Furthermore, we also observe that these preliminary rankings are themselves influenced by the majors of upperclass companymates. In other words, we observe herding behavior not just for final major choices by freshman, but also for preliminary major rankings by freshman (specific estimates not reported here). This has implications for our tale of inter-generational herding. The major selections of generation $t-1$ in reality influences the major selections of generation t in two ways: the direct influence on those in generation t who emulate those in generation $t-1$; and the indirect influence on those in generation t who emulate others in generation t who in turn emulate those in generation $t-1$. Together these results suggest that the peer-to-peer herding we observe is in large part a manifestation of inter-generational herding, and so this

[10] We observe such data for three fewer academic years, beginning in 1999.
[11] This is similar to what is done in Sacerdote (2001) and Di Giorgi et al. (2010).
[12] Here the contemporaneous herding effect is *negative*, but is only significant at the 10 percent level.

latter channel on which we are focused is even stronger.

5.2 Do Herders Perform Worse Than Non-Herders?

If herding behavior is a manifestation of "social learning," students can receive valuable information from their peers which can help them make better and more informed decisions. However, the signal students receive from peers may be an inferior signal relative to information about themselves. Furthermore, herders may also be motivated by joining a social network, which may not be conducive to doing well academically.

An empirical investigation of this question is challenging because we do not observe student types. Given the data at hand we propose a way to (imperfectly) classify some students as herders while controlling for pre-existing characteristics.

Specifically we conduct a series of logit regressions using student-level data — one regression for each major m—in which we regress the binary choice of choosing major m on students' background (pretreatment) characteristics (X_i in equation [1]). From each regression — i.e., for each major m — we generate predicted probabilities that each student chooses major m. We then carry out a similar series of logit regressions but now add a covariate for the proportion of upperclass companymates who chose major m ($\frac{\sum_k ECON_{kct}}{n_{ct}}$ in equation [1] when m refers to Economics). We again generate the predicted probabilities that each student chooses major m; these new probabilities still reflect each student's idiosyncratic chances of choosing major m but are now updated with exogenous information on peers' major allocation. We then subtract the first predicted probability from the second to obtain a measure of how much *more* likely a student is to choose major m when peer information is taken into account. Finally, we classify a student as a herder if she actually chose major m (*ex post*) *and* her predicted-probability-difference is in the top five percentile of the distribution across the whole sample. We additionally perform this classification for the top ten percentile of the distribution, as an alternate specification.

In summary, a student is labeled a herder if her *ex post* major choice is aligned with her *ex ante* likelihood of responding to her upperclass companymates' major choices. The approach benefits from exploiting information on the extent to which some majors naturally induce more herding, independent of the student's characteristics. Using this method with the five percent cutoff, 1,077 students are classified as herders and 22,206 are unclassified (2,145 and 21,138 with the ten percent cutoff).

We utilize these herder classifications and adopt the following regression framework for student i's grade in section s of course c in academic year t (note that here the full sample consists of grades in academic courses from *all* students, not just freshmen):

$$Grade_{icst} = \alpha_1 * Herder_i + X_i^{'}\beta + \theta * Major_i + \nu_{cst} + \mu_{icst} \tag{2}$$

$Herder_i$ is a binary indicator using either of the above definitions, X_i contains the usual set of pretreatment background characteristics, $Major_i$ is the set of binary major controls, ν_{cst} represents course-section by year fixed effects, and μ_{icst} is the individual specific error term.

OLS estimation of equation (2) might not cleanly identify a causal effect of the choice of being classified as a herder on grades in this context. On the one hand, omitted variables like effort and unobserved ability may bias estimates of α_1 in unclear directions; but on the other hand such bias may be minimal, as estimates are conditional on a host of observables—including math and verbal ability captured by SAT score, freshman-year grades, and fixed effects at the course-section level. Our measures are partly derived from *ex ante* exogenous variation in peers' major choices and partly derived from students' *ex post* major choices. Thus we cannot rule out that herder status is correlated with the error term, but we are reassured if results under various specifications and classification schemes all point in the same direction.

Conditional on these caveats, results from both classifications indicate that herding students tend to earn higher grades when they are in their respective majors. Being a herder is associated with a higher course grade by 0.01 to 0.015 grade points. The effect appears to dissipate by the time of one's senior year. The underlying cause remains unclear — herders may have learned from their peers which majors might best suit their skills or interest, or they may have learned which majors are the easiest. The point however is that it appears that they are learning. It does not appear that herders are sacrificing academic performance so they they can enjoy a larger social network.

Broadly, the effects of herding are small and, given challenges with identification, we cannot claim definitively that herding helps with student performance, but results do support the hypothesis. It is conceivable that larger effects might exist among the all-inclusive set of students who herd, if we were able to observe it.

5.3 Is It Social Learning or Network Externalities?

In this section we further explore the underlying mechanisms regarding students' incentives to herd.

5.3.1 Do Grade Signals Attenuate Herding?

So far we have focused strictly on peer signals in swaying students to pick majors, controlling for background characteristics. But for some majors, we may also explore the role of more accurate information regarding some majors from taking required freshman-year courses. As discussed in section 4.3, freshmen take a standardized set of courses before having to commit to a major at the end of their spring term. They take two semesters of chemistry, English, and mathematics. These provide freshmen personal signals regarding course content and their own abilities in these three areas during both the fall and spring semesters.

Further, freshmen must take one semester of political science (U.S. Government and Constitutional Development) and one semester of history (American Naval History). This provides additional signals regarding their abilities in non-STEM subjects. However, unlike chemistry, English, and math, half of the freshman class enrolls in the political science course in the fall and the history course in the spring, while the other half must take history in the fall and political science in the spring. This course allocation is done by company and is completely random, thus providing a source of exogenous variation in the *timing* of grade signals for these two subjects.

Connecting back to the model of section 6, a individual who only cared about grades is, for a given distribution of peers, less likely herd towards a major given more accurate information regarding that major. On other hand, someone interested only in the social network would not change herding behavior with better information. What happens to herding behavior with more reliable information is thus an empirical question.

Of particular interest to us are history or political science majors. Those students who are assigned political science (or history) the first semester essentially are forced to become better informed with respect to choosing political science (or history) as their major. Those that cannot take political science (or history) in the fall are less likely to have information with respect to choosing a major in political science (or history) and therefore will perhaps tend towards the influence of the past choices of their companymates.

To incorporate these features of the major choice decision, we consider the following expansion of equation (1) for those majors in which freshmen are required to take core courses in their first two semesters (history, political science, chemistry, English, and mathematics). Here X_{ict} includes the same background characteristics as before, as well as the additional covariate of student i's grade in the relevant major's core course. So if we consider history as one of these core disciplines, we estimate:

$$HIST_{ict} = \alpha + X_{ict}^{'}\beta + \delta \frac{\sum_k HIST_{kct}}{n_{ct}} + \eta_t + \epsilon_{ict}. \tag{3}$$

Table 8 displays the OLS estimates of equation (3) for the five majors listed above, stratified by fall and spring semesters. For instance, column 1 is estimated only on the subset of freshmen who were assigned to take American Naval History in the fall, while column 2 is estimated on those who took it in the spring. Column 5 is estimated on the set of freshmen who took chemistry in the fall, while column 6 is estimated on those who took it in the spring (note that the vast majority of students take chemistry during *both* semesters of freshman year, so these two sets will largely overlap). The table emphasizes coefficient estimates for the proportion of upperclass companymates in the major and the grades received for the required course in the major. Grade signals appear to provide a strong pull for each major; students who do well in a course tend to pick the major associated with that course. However grades are endogenous and their coefficients cannot be interpreted as causal. For instance, a student already planning to major in chemistry might exert extra effort in her introductory chemistry courses. In this case, the causality would run in the opposite direction, biasing estimates of the chemistry grade effect upwards. Despite this caveat, we do not estimate statistically significant peer effects in chemistry and English; these are examples of subjects where more accurate information exists, which may temper the potency of the herding behavior seen in other majors. We will return to discussing mathematics in the next section.

To uncover more concrete evidence of behavioral differences between informed and uninformed agents and how these differences may affect the herding process (already seen in Tables 4 and 5), we examine the history and political science columns of Table 8. Here we find no statistically significant evidence that those who take the American Naval History or U.S. Government and Constitutional Development during the fall term utilize the peer signal in choosing to major in history or political science, respectively. If they take the subject during the spring term, on the other hand, the peer signal becomes positive, large, and statistically significant, while the grade signal attenuates. This makes sense since in the case of the spring semester, the final grade signal for the subject will not materialize before one must choose a major. Thus we see another example where peer signals can provide an alternative to grade signals when these signals are noisy or not available. This is in essence the empirical validation of our conceptual framework.[13] It constitutes another piece of evidence that social learning is a key factor in producing herding behavior.

5.3.2 Does Social Network Stability Affect Herding?

As mentioned earlier, some students are relocated to a different dormitory after their freshman year; others remain at the same dormitory all four years. Is there a statistically significant increase in herding for those whose social network is stable?

To explore this question, Table 9 now splits the sample between the shot-gun period (where the social network is disrupted annually) and the non-shot-gun period (where the social network is stable) and again estimates equation (1) using full upperclass companymate peer effects. Comparing these results with those of Table 4 is illuminating. Here we see that there are four majors with statistically significant herding estimates during the shot-gun period, and six majors with statistically significant herding estimates during the non shot-gun period. Which major exhibits herding during each period appears fairly random.

Further, we test for a statistically significant increase in herding behavior when there is a regime switch to halting shotguns. The p-values from these tests (of statistical difference between the coefficients across the two subsamples) are displayed in Table 9; they are fairly uniformly distributed. For nearly all majors, we cannot reject the hypothesis that the change in herding behavior when the social network stabilizes is

[13] See Proposition 1 in the appendix for a more formal discussion.

anything other than zero. We additionally depict these findings in Figure 4, which shows point estimates and 90% confidence intervals for peer effects for all majors, again stratified by shot-gun era. This would suggest that the value of network externalities does not rise with the stabilization of the social network.

We observe one important exception — mathematics. The math major is unique in a number of ways. One, all students are required to take two semesters of math before choosing a major; thus students receive strong personal signals regarding their math ability and interest. Two, a demonstrated ability in math signals an ability to perform well in a *range* of majors, not just math. Indeed, "a knowledge of mathematics is, in fact,...a gateway into STEM fields."[14] In order to select math as a major, a demonstrated proficiency may not be enough given so many other options. Thus it makes sense that students would need greater motivation related to the social network in order to continue studying a subject with a wide range of applications. We suggest that the value of network externalities can rise with social stability for a broad subject area like mathematics.

To further unpack the role of social stability, we perform two other exercises. First, we re-estimate our binary choice models where the choice is among one of the three groups (engineering, math/science, and humanities/social sciences), but split our sample between shotgunned and non-shotgunned cohorts. Results are presented in Table 10. Here we see that the positive herding towards group I majors remains consistent whether or not the social network is stable. We also see that herding does not occur for the more heterogeneous groups II and III in either shotgun regime.

Second, we estimate herding effects for those majors whose courses are taken by freshmen (i.e. we estimate equation [3]), with split samples for both shot-gun/non shot-gun periods, and as before observe grade and herding effects for both fall and spring semesters. Results are presented in Table 11. First, notice that when comparing the shotgun versus no shotgun periods for History and Political Science, the role of grade signals in limiting herding behavior does not weaken in the no shotgun period. This would once again suggest that the value of network externalities does not rise with the stabilization of the social network.

On the other hand, it is clear that we estimate a statistically significant increase in herding towards the math major when the social network stabilizes (see p-value columns for tests of statistical difference of coefficients across the two eras). This finding is robust for either semester. Although the estimates are not as precise, English is also something of a fundamental subject, one where skills can be deployed in writing intensive courses, though given its engineering bent the Naval Academy does not have as many of these opportunities for students as those for math.[15] Thus, when faced with many alternatives, a robust social net-

[14] from the American Mathematical Society blogpost titled "On Teaching and Learning Mathematics," posted February 14, 2019.

[15] When Gallup asked Americans what they considered to be the most "important" subject, meaning most valuable and applicable to life's activities, 34 percent of respondents said math, followed by English at 24 percent, history at 7 percent, and sciences at 4 percent. (https://news.gallup.com/poll/164249/americans-grade-math-valuable-school-subject.aspx)

work may be needed to entice someone to specialize in something foundational (like fast people joining Track and Field as opposed to any other sport where running matters, or analytically-minded people becoming professors in economics as opposed to doing economic analysis in public or private sector employment.)

Overall this is the first work to allow a glimpse into the potential mechanisms behind herding through this natural experiment of network disruption. Evidence from this experiment suggests that the social network motivation for herding is weak to non-existent for the vast majority of majors. For foundational subjects, however, the social network may play an important role.

5.3.3 Does Homophily Affect Herding?

We can also use the empirical framework of equation (3) to test for "homophily" effects — that is, herding towards individuals with some similar underlying characteristic. We look at two: gender and race.

Specifically, we first bifurcate the peer effect term into male and female upperclass companymate groups, and we allow the corresponding peer effect coefficients (δ) to differ by own gender. We also allow the grade signal coefficient to differ by own gender. Results are presented in Table 12.

Across all five majors and both fall and spring semesters, we find no evidence that women are more likely to herd than men. The apparent lack of "female-to-female pull" runs counter to the findings of Carrell et al. (2010), albeit within the somewhat different peer-to-peer context (as opposed to instructor-to-peer, as they study).

The detectable peer effects in major choice stem from male upperclass companymates who comprise the majority of all students. We estimate statistically significant effects for both men (in history, political science, and math) and women (in English).

Additionally, the correlation between grade signal and major choice is notably stronger for women (versus men) in STEM fields, while its relative strength (versus men) is mixed in non-STEM fields. As discussed above, while we cannot claim to identify causal grade effects in this context, these findings run counter to those of Rask (2010). They do however support Goldin (2015), which suggests that females may have greater sensitivity to initial grade signals than males when choosing academic majors, particularly in technical fields.[16] Overall, this exercise highlights the challenge of encouraging more women to choose STEM majors; stronger-than-average grade signals might be required, and there is no evidence that herding behavior could be easily exploited to advance this goal.

Finally, we perform a similar exercise, but now we bifurcate the peer effect term into white and minority-race groups. Results are reported in Table 13 Similar to our findings on gender, we find no evidence that

[16] Specifically, the paper studies the role of grade signals for a Principles of Economics course in a highly selective liberal arts college, noting that poor initial grades dissuade women from pursuing an economics degree more than men. Our study here suggests that this may be a wider phenomenon than just for economics degrees.

minorities are more likely to herd than white students, nor do we find that minority students herd more towards those of similar race. This again points to limited network externalities in herding behavior. If we believe that students feel socially more comfortable with those of the same race (Byrd, 2017) or the same gender (Canada and Pringle, 1995), we would imagine homophily herding to occur only if herding was motivated by network externalities. This does not appear to be the case.

5.4 Empirical Test of a Dynamic Externality

The analysis of the previous section suggests that for nearly all major choices, network externalities are not much of a motivator. Along with this it appears that herders tend to perform better academically (Table 7), particularly early on in their major-specific coursework.

One issue this raises is how the decision of one person to herd influences others in subsequent generations, potentially creating an inter-generational information spillover. While in Banerjee (1992) once a sufficient number of people choose a thing (whether rightly or wrongly) all subsequent generations will herd towards that thing, in reality other corrective factors may counter this. To test for this dynamic externality, we estimate an autoregressive model on various subsamples of the dataset that allow us to compare the period of academic years with shot-guns to the period without them. The latter period may have prevented herders (and hence herding behavior) from accumulating inter-generationally within companies over the years.

Let Num_{mct} represent the number of students in company c in class-year t who majored in major m. The model is a simple autoregression of Num_{mct} on some number of its lags, as well as fixed effects for company, class-year, and major:

$$Num_{mc,t} = \beta_1 * Num_{mc,t-1} + \ldots + \beta_k * Num_{mc,t-k} + \gamma_m + \epsilon_c + \psi_t + \mu_{mc,t} \tag{4}$$

OLS estimates in Table 15 display evidence that herding is persistent but only after shot-guns ceased for the class of 2007 and later. Columns 1 and 4 indicate that herding is much more persistent after shot-guns cease. In column 1 we estimate equation (4) on the graduating classes prior to 2007, who experienced shot-guns. Here we expect no autocorrelation within companies across years; the only positive and statistically significant effect comes from the junior cohort, but note that this is relatively small and is only significant at the 10% level. In column 4, estimated on the class-years who were not shot-gunned, the positive herding effects are much more precisely estimated, and they correspond to our previous findings on herding behavior in Tables 4 and 5: seniors and sophomores have the strongest impact on freshman major choices; for example, ten additional sophomore companymates in a given company and major lead to just under one additional freshman in that company choosing that major. Interestingly, column 1 also indicates that under shot-guns, more juniors within a company/major bin leads to *fewer* freshmen in that bin the following year. This may imply some sort of "regression to the mean" effect occurring across companies due to shot-guns, particularly because the effect vanishes in column 4. We see a similar negative effect for the four-years-ahead ($t-4$, meant to be a "placebo group" because these cohorts would have graduated before the corresponding freshmen arrived at USNA) in column 1 but no effect in column 4 (as expected).

In columns 2 and 5 we stratify the sample to include only the majors where we detected statistically significant herding behavior (seen in Tables 4 and 5). Here the estimates are predominantly stronger and more precisely estimated compared to from columns 1 and 4. In columns 3 and 6 we estimate the model on the majors where we did not previously detect herding behavior. As anticipated, the effects are generally weaker and less significant than before.

Herding behavior is in a sense contagious. This could be a good thing or a bad thing. A piece of misinformation regarding major choices provided to one generation of students could lead to poor choices for this and subsequent generations of students. On the other hand, one could imagine a policy where one cohort of freshmen are given a great deal of information regarding all major choices (say by sampling a wider variety of entry-level courses), but subsequent generations given limited information. Given the potential for informational spillovers, this could be a more cost-effective way for students across multiple years to pick "correctly," even when faced with limited information.

6 Conclusion

We have demonstrated in this paper that students tend to emulate their predecessors in picking college majors. More importantly perhaps, we try to understand why. Given random disruptions to social networks, we conclude that students herd towards others mainly through social learning – they use peers to try to better match with an appropriate discipline, not merely to expand their social network. This tends to occur in the face of limited information about all the choices. It may also happen when freshmen face academic challenges unrelated to their own academic abilities that result in poor grades (such as adjustment to college life or other personal difficulties which we do not observe).

Freshmen tend to follow sophomores the most, who are closest in age and social standing but also the least informed regarding major subjects among all upper-classmates. This may be why the positive grade impacts for herders are small. A natural policy implication from this is the need to better inform students regarding their choices. Our model and empirics imply this would be unambiguously welfare-enhancing — by revealed preferences students do not appear to derive benefits through network externalities. Greater information obviates the need for noisier information from peers. On the other hand the presence of a dynamic information externality implies not every generation needs to be equally informed. Lessons here may be applied to many other areas where consumers face a menu of choices with limited information. These consumers may then be compelled to follow the choices of others, who themselves may or may not be well-informed.

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Appendix — A Simple Model of Herding

Consider a discrete choice extension of Banerjee (1992). In this case we will solely focus on a binary case, where each person sequentially chooses between two options, each hidden behind a door. Behind one door is a red ball, behind the other is a blue ball.[17] Each individual is either a Red person or a Blue person, but does not know which in advance. Each person's objective is to choose their own color. If they choose correctly they receive a prize of $\bar{z}$; if they choose incorrectly they receive nothing.

Similar to Banerjee (1992), we assume that each person receives a signal with probability α over which ball is behind which door; however the signal will be correct only with probability β, where $0 < \alpha < 1$, and $0.5 < \beta < 1$. Thus each person knows with certainty which ball is behind each door with probability $\alpha\beta$. Finally the fraction of people who are Red is $\gamma > 0.5$, whose value is known by all. Thus everyone believes they are more likely to be Red than Blue, and so everyone is trying to get the red ball.

This is a convenient conceptual framework given our empirical setting. Incoming freshmen face two sources of uncertainty — what is involved with each major (subject-matter, difficulty, long-run returns) and the degree of "fit" of the person to each major. They may or may not receive different types of signals regarding major choices (from friends, parents, advisers, and so on). These "α's" are unobserved by us. But for some choices, the accuracy of this information is boosted by course exposure (an increase in β). Our setting is also sequential, as freshmen observe the choices made by prior generations.

Consider the first person in the sequence. If she receives a signal she acts on it, if she doesn't she flips a coin. Now consider the second person in the sequence. Suppose he observes that the first person chose the first door. If he does not receive a signal, he will also choose the first door. What if however he gets a signal that suggests that the red ball (which he believes has the higher likelihood of being right ball for him) is behind the other door?

Here we can use a Bayesian approach: Let X be the event that person 1 picks the first door. Let Y be the event that person 2's correct pick is the first door. Then:

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X|Y)P(Y) + P(X|\tilde{}Y)P(\tilde{}Y)} \tag{5}$$

Assuming that person 2 is likewise agnostic (so that $P(Y) = P(\tilde{}Y) = 0.5$), this simplifies to

[17]The framework can easily be extended to include a greater array of choices (Green, Purple, etc.), complicating the math but retaining the key propositions.

$$P(Y|X) = \frac{P(X|Y)}{P(X|Y) + P(X|\tilde{}Y)} \tag{6}$$

For this second person, each conditional probability on the right-hand-side can be written as

$$P(X|Y) = (\gamma\alpha\beta) + ((1-\gamma)\alpha * (1-\beta)) + (0.5(1-\alpha)) \tag{7}$$

$$P(X|\tilde{}Y) = (\gamma\alpha(1-\beta)) + ((1-\gamma)\alpha\beta) + (0.5(1-\alpha)) \tag{8}$$

In equation (7), the first term is the probability that person 1 received the correct signal and that person 2 is red. The second term is the probability that person 1 received an incorrect signal, but person 2 happens to be blue. The final term is the likelihood that person 1 has no information and randomly chose the right door for person 2. Parallel logic applies for equation (8).

Lemma 1. *Person 2 will act on his signal if and only if* $\beta > \beta^* = \frac{\alpha - 2\alpha*\gamma - 3}{2\alpha - 4\alpha\gamma - 2\gamma}$.

That is, person 2 will not herd so long as the accuracy of his signal is large enough.

Suppose now that person 3 in the sequence arrives finding two people having picked the first door, and her signal indicating the red ball is behind the second door. Now let X be the event that both people pick door 1, and let Y be the event that person 3's correct pick is the first door. Again assume that person 3 is agnostic. Then:

$$\begin{aligned} P(X|Y) = {} & \gamma\left[(\alpha\beta)^2 + \alpha\beta(1-\alpha) + (1-\alpha)(0.5\alpha\beta + 0.5(1-\alpha))\right] \\ & + (1-\gamma)\left[\alpha(1-\beta)^2 + \alpha(1-\beta)(1-\alpha) + (1-\alpha)(0.5\alpha(1-\beta) + 0.5(1-\alpha))\right] \end{aligned} \tag{9}$$

and

$$\begin{aligned} P(X|\tilde{}Y) = {} & \gamma\left[(\alpha(1-\beta))^2 + \alpha(1-\beta)(1-\alpha) + (1-\alpha)(0.5\alpha(1-\beta) + 0.5(1-\alpha))\right] \\ & + (1-\gamma)\left[(\alpha\beta)^2 + \alpha\beta(1-\alpha) + (1-\alpha)(0.5\alpha\beta + 0.5(1-\alpha))\right] \end{aligned} \tag{10}$$

Each conditional probability is a function of various combinations of person 3 being red or blue, person 1 choosing correctly or incorrectly, and person 2 receiving a signal or copying person 1. Whether or not person 3 herds and chooses door 1, or goes with her signal and chooses door 2, is likewise a Bayesian calculation given by (6).

Lemma 2. *Person 3 will act on his signal if and only if*

$$\beta > \hat{\beta} = \frac{\sqrt{(16\alpha^2 + 16\alpha + 4)\,\gamma^2 + (-8\alpha^3 - 4\alpha^2 - 4\alpha)\gamma + \alpha^4 + 6\alpha^3 - 23\alpha^2} - (4\alpha - 2)\gamma + \alpha^2 - \alpha}{4\alpha^2}$$

Lemma 3. $\beta^* < \hat{\beta}\ \forall\ 0 < \alpha < 1$ *and* $\gamma > 0.5$.

This simply shows that two peers produce a more compelling reason for individuals to herd and not follow their own signal than one. We can generalize this result as follows:

Proposition 1. *Let* $\tilde{\beta_n}$ *be the threshold level of signal accuracy for person* n *not to herd. For* $n - 1$ *peers that have chosen door 1 and person* n *having received a signal that door 2 contains the red ball,* $\tilde{\beta_n}$ *rises with* $n\ \forall\ \tilde{\beta_n} < 1$ *.*

In other words, the more peers bunch towards a particular choice, the greater signal accuracy required to avoid herding by the next decision-maker. On the one hand, as information for everyone improves (increases in β), it becomes less likely that your peers had herded, thus improving the herd signal and allowing you to yourself herd. On other hand as information improves your personal signal strengthens more than the peer signal (your peers after all might have just guessed). For all $\beta < \tilde{\beta_n}$ the former effect is larger than the latter effect. Illustrations for the above mentioned cases are given in Figures 5-6.

This simple proposition leads to some empirically testable hypotheses. First, all else equal, each extra peer choosing something will raise the probability of someone from the next generation choosing the same thing. Second, given a certain number of peers choosing something, greater information about the choices will lower the pull of these peers.

Extension — Network Externalities

We may also consider the possibility that there are extra gains for person 3 to pick the more popular choice. Becker (1991) for example develops a model of network effects where the demand for a good by a person depends positively on the aggregate quantity demanded of the good, hypothesizing that "the pleasure from some goods is greater when many people want to consume it." In this spirit consider now utility of person n

person being $z^{\delta}n^{1-\delta}$, where z is the prize given in each option, and $0 < \delta < 1$. Now person n must calculate expected utilities for choosing between door 1 that has been chosen by $n-1$ peers, and door 2 for which n's personal signal suggests the right choice.

Assume that choosing incorrectly gives a normalized z payout of 1, so that $\bar{z} > 1$. Consider person 3. Her expected utility from choosing door 1 is $P(Y|X)\bar{z}^{\delta}3^{1-\delta} + (1 - P(Y|X))3^{1-\delta}$, where $P(Y|X)$ is calculated using (9) and (10). Her expected utility from choosing door 2 on the other hand is $\beta\gamma\bar{z}^{\gamma}$.

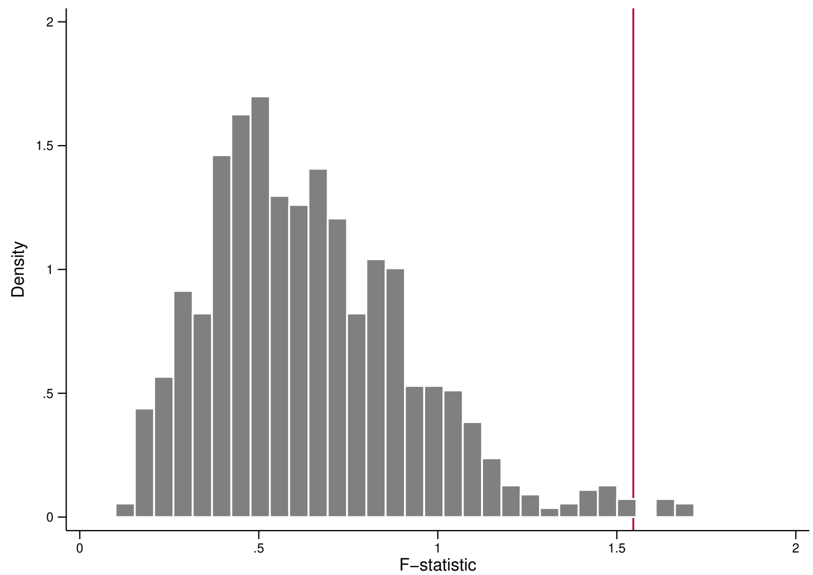
Proposition 2. $\frac{\partial\tilde{\beta_n}}{\partial\delta} > 0 \; \forall \; \tilde{\beta_n} < 1$.

In words, stronger network externalities raises the knowledge threshold needed to stop herding. In Figure 7 we show network effects strong enough so that herding occurs no matter the level of signal accuracy.

Our empirical set-up provides us a unique way to test the effects of better information (with majors with first-semester exposure proxying for high β, and majors without such exposure proxying for low β), and the effects of stronger network externalities (with class years undergoing a shotgun proxying for low γ, and class years with stable social networks proxying for high γ) on herding behavior.

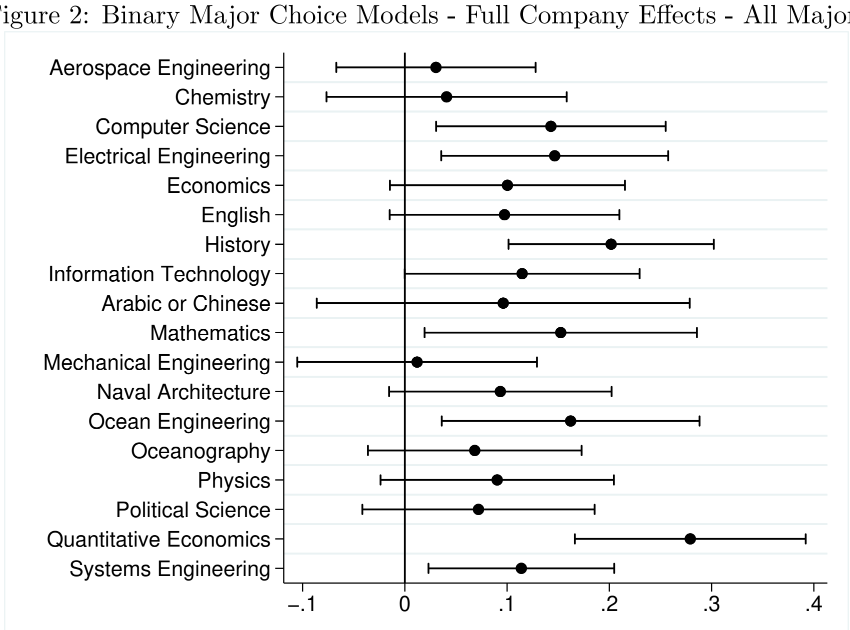
7 Figures

Figure 1: Test of Exogeneity of Upperclass Companymates' Majors



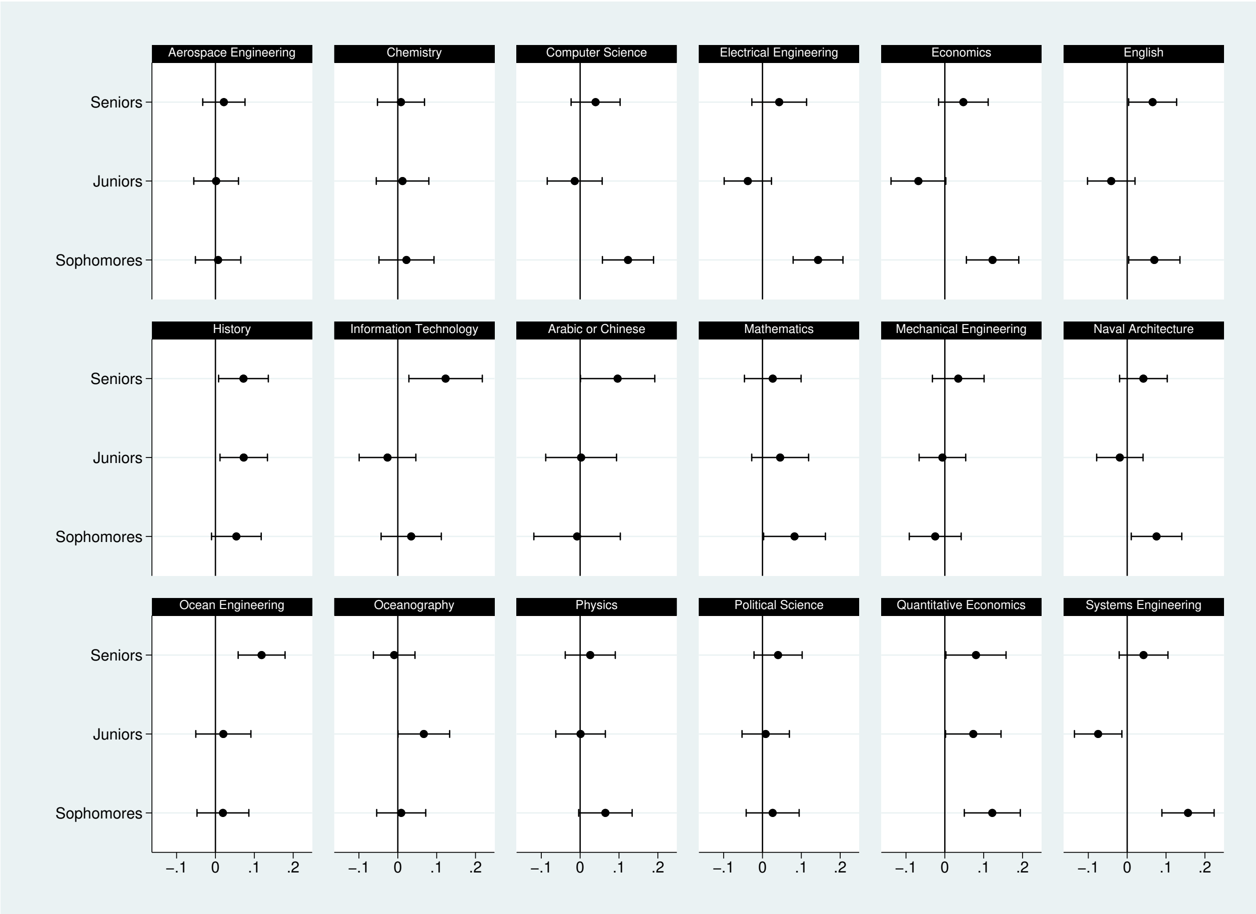
Note: Figure shows a histogram of F-statistics generated from the process described in section 4.3. The vertical line indicates the critical value for an $F(12, \infty)$ distribution at a 10 percent level of significance. F-statistics generated from the series of regressions are predominantly less than the critical value, indicating that observable pretreatment characteristics are not correlated with the major choices of a freshman's upperclass companymates.

Figure 2: Binary Major Choice Models - Full Company Effects - All Majors



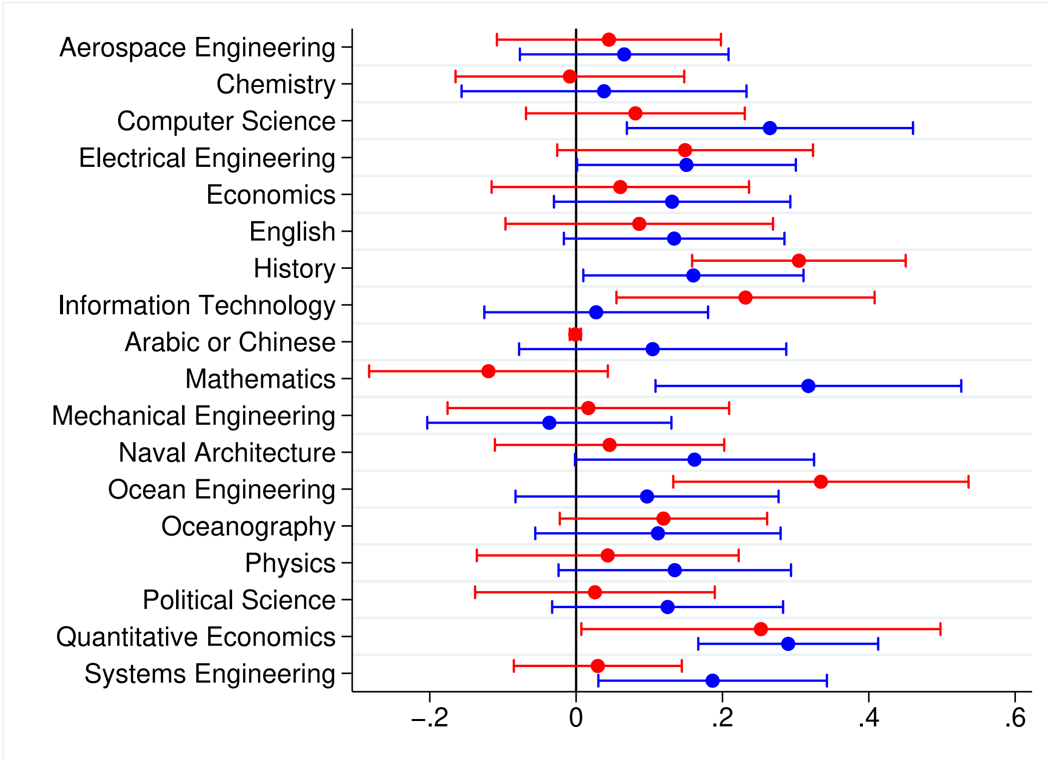
Note: Figure displays OLS point estimates of the full upperclass peer effect δ from equation (1) along with 90% confidence bands for all 18 majors.

Figure 3: Binary Major Choice Models - Company Effects by Class Year - All Majors



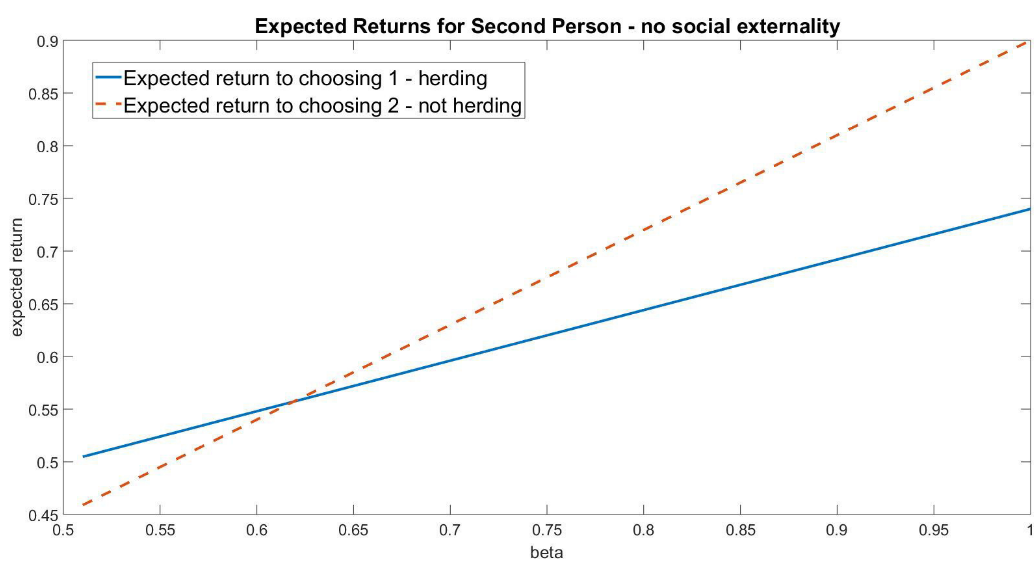
Note: Figure displays OLS point estimates of the upperclass peer effect δ from equation (1) — now broken out by upperclass-year-cohorts — along with 90% confidence bands for all 18 majors.

Figure 4: Binary Major Choice Models - Company Effects by Class Year - All Majors



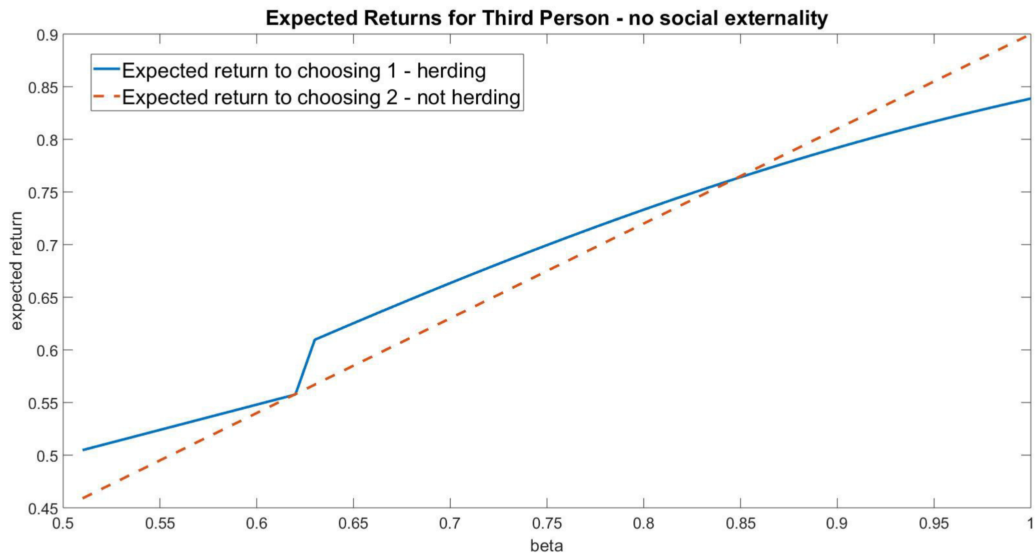
Note: Figure displays OLS point estimates of the upperclass peer effect δ from equation (1) — with the sample now stratified by shot-gun eras — along with 90% confidence bands for all 18 majors. Red bands denote shotgun era; blue bands denote post-shotgun era.

Figure 5: Expected returns for person 2



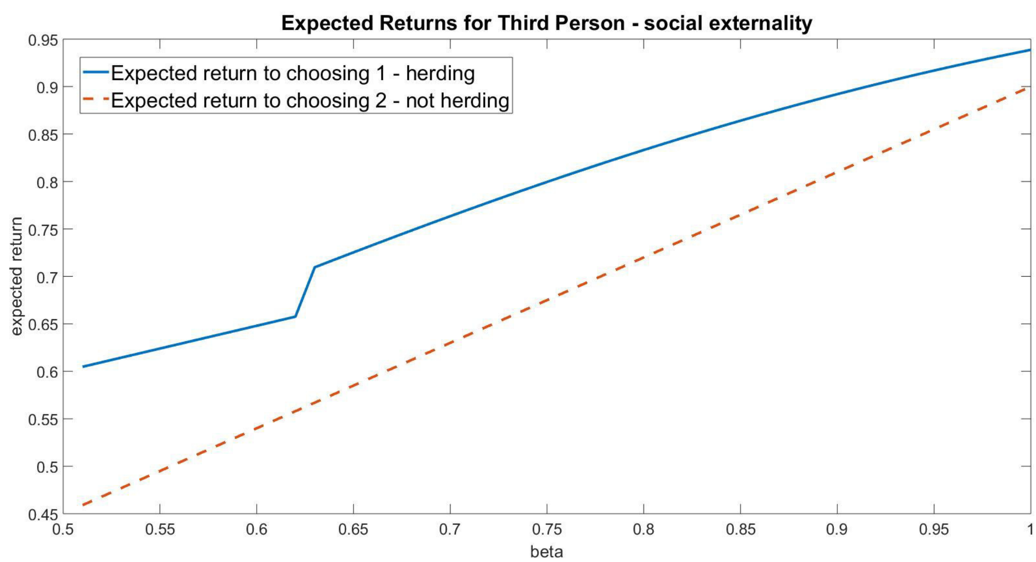
Note: With just one peer, the threshold for signal accuracy to combat herding is fairly low ($\tilde{\beta}_1 \approx 0.62$).

Figure 6: Expected returns for person 3



Note: With two peers, the threshold for signal accuracy is higher ($\tilde{\beta}_2 \approx 0.85$).

Figure 7: Expected returns for person 3 with social externalities



Note: Here we show that with a high-enough δ, the person will herd no matter the quality of the signal.

8 Tables

Table 1: Summary Statistics - Student-semester-level

	Mean	Std.Dev.
Female (binary)	0.19	0.39
Age (at arrival date)	18.8	0.94
Race/ethnicity:		
White	0.73	0.44
Black	0.06	0.24
Asian	0.04	0.20
Hispanic	0.10	0.30
Recruited (binary)	0.28	0.45
Prior enlisted (binary)	0.07	0.25
Feeder status:		
Direct	0.75	0.43
NAPS	0.18	0.38
Foundation	0.05	0.23
Other	0.02	0.12
SAT math	665	71.3
SAT verbal	641	76.1
Academic GPA	2.79	0.71
Military GPA	3.06	0.53
Observations	46131	

Note: Student-semester-level summary statistics for all freshmen in academic years 1996-2015.

Table 2: Summary Statistics - Major Counts - Academic Years 1996-2015

Major Name	Number of Graduates	Percentage
Aerospace Engineering	2,632	5.69
Chemistry	1,297	2.8
Computer Science	1,592	3.44
Electrical Engineering	1,140	2.46
Economics	5,072	10.96
English	2,742	5.92
History	3,682	7.96
Information Technology	786	1.7
Arabic or Chinese	362	0.78
Mathematics	1,770	3.82
Mechanical Engineering	3,056	6.6
Naval Architecture	1,026	2.22
Ocean Engineering	2,216	4.79
Oceanography	2,838	6.13
Physics	1,046	2.26
Political Science	6,095	13.17
Quantitative Economics	1,344	2.9
Systems Engineering	4,023	8.69
Other*	3,561	7.69

Note: Tabulation of final major choices for all students who remained enrolled through major selection during March of freshman year. *Other category includes small majors such as computer engineering, nuclear engineering, and cyber science, as well as "general science" and "general engineering" — for students who complete their Bachelor's degree but fail to satisfy a particular major's requirement (this requires special Dean's approval) — and students who separated from USNA before selecting a major.

Table 3: School-major Choice Models

Choice of major in School:	Engineering	Math and Science	Humanities and Social Sciences
Proportion of upperclass	**0.191*** **	**0.0747**	**0.0635**
companymates in same School-major	**(0.0665)**	**(0.0735)**	**(0.0622)**
Female (binary)	-0.0811***	0.0903***	-0.000702
	(0.00687)	(0.00763)	(0.00796)
Age (at arrival date)	-0.0143***	-0.0113**	0.0213***
	(0.00506)	(0.00501)	(0.00520)
Race/ethnicity (ref.: white)			
Black	-0.0304***	-0.00673	-0.0549***
	(0.0107)	(0.0125)	(0.0136)
Asian	-0.0462***	0.0313**	0.00659
	(0.0143)	(0.0148)	(0.0146)
Hispanic	-0.0410***	0.00170	0.0180*
	(0.00946)	(0.00959)	(0.0108)
Additional controls	Y	Y	Y
Academic year FE	Y	Y	Y
Observations	23274	23274	23274
R^2	0.103	0.022	0.118

Note: $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$. Linear probability estimates of the choice of majoring within a School at USNA (Engineering, Math and Science, or Humanities and Social Science) versus choosing either of the other two Schools. Choice is modeled as a function of observable characteristics and (exogenous) proportion of upperclass companymates who chose that School (which captures the reduced form peer effect of the influence of upperclass companymates on major selection). Additional controls (not shown to preserve space) include: recruited athlete status, prior enlistment status, feeder source, SAT math score, SAT verbal score. Standard errors are clustered by academic year by company groups.

Table 4: Binary Major Choice Models - Full Company Effects

Major choice:	Com. Sci.	Elec. Eng.	History	Math	Ocean Eng.	Q. Econ.	Sys. Eng.
Prop(upperclass	**0.143****	**0.147****	**0.202*****	**0.152***	**0.162****	**0.279*****	**0.114****
companymates in major)	**(0.0682)**	**(0.0674)**	**(0.0609)**	**(0.0808)**	**(0.0765)**	**(0.0685)**	**(0.0551)**
Female (binary)	-0.0233***	-0.00469**	-0.0428***	0.0266***	0.0110***	-0.00951***	-0.0367***
	(0.00253)	(0.00210)	(0.00435)	(0.00394)	(0.00387)	(0.00256)	(0.00405)
Age (at arrival date)	-0.00544**	0.00262	-0.000688	0.000196	-0.00133	-0.000973	-0.00844***
	(0.00217)	(0.00241)	(0.00313)	(0.00227)	(0.00244)	(0.00179)	(0.00309)
Race/ethnicity (ref.: white)							
Black	0.0132**	0.00663*	-0.0455***	0.0195***	-0.0305***	-0.000738	0.0111
	(0.00523)	(0.00373)	(0.00705)	(0.00537)	(0.00398)	(0.00490)	(0.00726)
Asian	0.0150**	0.0122*	-0.00636	0.00230	-0.0144**	0.00226	0.0110
	(0.00707)	(0.00653)	(0.00763)	(0.00710)	(0.00625)	(0.00598)	(0.0103)
Hispanic	0.0112**	-0.00645**	-0.00395	0.00719	-0.0115***	-0.00769**	-0.00837
	(0.00450)	(0.00296)	(0.00643)	(0.00470)	(0.00439)	(0.00330)	(0.00587)
Additional controls	Y	Y	Y	Y	Y	Y	Y
Academic year FE	Y	Y	Y	Y	Y	Y	Y
Observations	23274	23274	23274	23274	23274	23274	23274
R^2	0.016	0.023	0.032	0.020	0.008	0.010	0.028

Note: $^{*}p < .10,^{**}p < .05,^{***}p < .01$. Table shows binary choice models for majors in which we detect statistically significant peer effects. Table contains linear probability estimates of the choice of each major (versus any other major) as a function of observable characteristics and (exogenous) proportion of upperclass companymates who chose that major (which captures the reduced form peer effect of the influence of upperclass companymates on major selection). Additional controls (not shown to preserve space) include: recruited athlete status, prior enlistment status, feeder source, SAT math score, SAT verbal score. Standard errors are clustered by academic year by company groups.

Table 5: Binary Major Choice Models - Company Effects by Class Year

Major choice:	Com. Sci.	Elec. Eng.	Econ.	English	History	Info. Tech.
Prop(seniors in major)	**0.0398**	**0.0431**	**0.0477**	**0.0655***	**0.0721***	**0.123****
	(0.0383)	**(0.0428)**	**(0.0387)**	**(0.0375)**	**(0.0388)**	**(0.0574)**
Prop(juniors in major)	**-0.0140**	**-0.0378**	**-0.0680**	**-0.0409**	**0.0728***	**-0.0265**
	(0.0429)	**(0.0370)**	**(0.0428)**	**(0.0371)**	**(0.0371)**	**(0.0443)**
Prop(soph. in major)	**0.123*****	**0.143*****	**0.123*****	**0.0699***	**0.0538**	**0.0345**
	(0.0400)	**(0.0389)**	**(0.0409)**	**(0.0400)**	**(0.0388)**	**(0.0470)**
Additional controls	Y	Y	Y	Y	Y	Y
Academic year FE	Y	Y	Y	Y	Y	Y
Observations	23274	23274	23274	23274	23274	23274
R^2	0.016	0.023	0.056	0.053	0.032	0.015

Major choice:	Lang.	Math	Nav. Arch.	Ocean Eng.	Q. Econ.	Sys. Eng.
Prop(seniors in major)	**0.0965***	**0.0264**	**0.0418**	**0.119*****	**0.0802***	**0.0422**
	(0.0580)	**(0.0442)**	**(0.0372)**	**(0.0366)**	**(0.0470)**	**(0.0381)**
Prop(juniors in major)	**0.00257**	**0.0455**	**-0.0188**	**0.0203**	**0.0732***	**-0.0747****
	(0.0553)	**(0.0444)**	**(0.0362)**	**(0.0430)**	**(0.0433)**	**(0.0371)**
Prop(soph. in major)	**-0.00788**	**0.0825***	**0.0755***	**0.0192**	**0.122*****	**0.157*****
	(0.0675)	**(0.0483)**	**(0.0395)**	**(0.0405)**	**(0.0438)**	**(0.0408)**
Additional controls	Y	Y	Y	Y	Y	Y
Academic year FE	Y	Y	Y	Y	Y	Y
Observations	23274	23274	23274	23274	23274	23274
R^2	0.013	0.020	0.005	0.008	0.010	0.029

Note: $^{*}p < .10,^{**} p < .05,^{***} p < .01$. Table shows binary choice models for majors in which we detect statistically significant peer effects. Table contains linear probability estimates of the choice of each major (versus any other major) as a function of observable characteristics and (exogenous) proportion of upperclass companymates who chose that major (which captures the reduced form peer effect of the influence of upperclass companymates on major selection). Proportion of upperclassmates in major is now divided into three class-specific variables. Additional controls (not shown to preserve space) include: gender, age upon arrival at USNA, race/ethnicity, recruited athlete status, prior enlistment status, feeder source, SAT math score, SAT verbal score. Standard errors are clustered by academic year by company by class year groups.

Table 6: Binary Major Choice Models - Company Effects with Freshman Preliminary Choice

Major choice:	Aero. Eng.	Com. Sci.	Elec. Eng.	Econ.	History	Info. Tech.	Math.
Prop(upperclass companymates in major)	**0.0459**	**0.167****	**0.145***	**0.0718**	**0.225*****	**0.112***	**0.157***
	(0.0685)	**(0.0765)**	**(0.0736)**	**(0.0732)**	**(0.0652)**	**(0.0659)**	**(0.0868)**
Avg. "score" of freshman companymates' prelim. pref. for this major	**-0.0169***	**-0.00465**	**0.00111**	**0.0179****	**0.00352**	**0.0268****	**0.0203*****
	(0.00862)	**(0.00919)**	**(0.00754)**	**(0.00831)**	**(0.00914)**	**(0.0128)**	**(0.00774)**
Additional controls	Y	Y	Y	Y	Y	Y	Y
Academic year FE	Y	Y	Y	Y	Y	Y	Y
Observations	20082	20082	20082	20082	20082	20082	20082
R^2	0.030	0.016	0.022	0.059	0.034	0.013	0.021

Major choice:	Mech. Eng.	Nav. Arch.	Ocean Eng.	Oceanog.	Q. Econ.	Sys. Eng.
Prop(upperclass companymates in major)	**-0.000140**	**0.119***	**0.161****	**0.102**	**0.262*****	**0.0939***
	(0.0756)	**(0.0663)**	**(0.0724)**	**(0.0647)**	**(0.0669)**	**(0.0537)**
Avg. "score" of freshman companymates' prelim. pref. for this major	**0.0122***	**0.0229*****	**0.0336*****	**0.0194****	**0.0131***	**0.0237*****
	(0.00711)	**(0.00768)**	**(0.00710)**	**(0.00861)**	**(0.00704)**	**(0.00812)**
Additional controls	Y	Y	Y	Y	Y	Y
Academic year FE	Y	Y	Y	Y	Y	Y
Observations	20082	20082	20082	20082	20082	20082
R^2	0.025	0.005	0.010	0.044	0.008	0.026

Note: $^{*}p < .10,^{**}p < .05,^{***}p < .01$. Table shows binary choice models for majors in which we detect statistically significant peer effects. Table contains linear probability estimates of the choice of each major (versus any other major) as a function of observable characteristics and (exogenous) proportion of upperclass companymates who chose that major (which captures the reduced form peer effect of the influence of upperclass companymates on major selection). This model includes an additional peer effect channel: the average "ranked score" of the major within one's freshman companymates' preliminary major preference ranking. Additional controls (not shown to preserve space) include: gender, age upon arrival at USNA, race/ethnicity, recruited athlete status, prior enlistment status, feeder source, SAT math score, SAT verbal score. Standard errors are clustered by academic year by company by class year groups.

Table 7: Grade Performance of Herders

	Five percent cutoff		
Subsample:	Sophomores	Juniors	Seniors
Dep. Var.: Course Grade	(1)	(2)	(3)
Herder (ref.: otherwise)	**0.0146****	**0.0142***	**-0.00519**
	(0.00735)	**(0.00763)**	**(0.00758)**
Additional controls	Y	Y	Y
Freshman-year GPA controls	Y	Y	Y
Academic major controls	Y	Y	Y
Course-section by year FE	Y	Y	Y
Observations	205947	189764	172877
R^2	0.385	0.319	0.223
	Ten percent cutoff		
Subsample:	Sophomores	Juniors	Seniors
Dep. Var.: Course Grade	(4)	(5)	(6)
Herder (ref.: otherwise)	**0.0128****	**0.0110****	**-0.00721**
	(0.00541)	**(0.00557)**	**(0.00556)**
Additional controls	Y	Y	Y
Freshman-year GPA controls	Y	Y	Y
Academic major controls	Y	Y	Y
Course-section by year FE	Y	Y	Y
Observations	205947	189764	172877
R^2	0.385	0.319	0.223

Note: $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$. Table contains OLS estimates of equation (2). Each column stratifies the sample by students' class years (after freshman year). The top set of results uses a five percent cutoff rule (see section 5.2), and the bottom set uses a ten percent cutoff. Additional controls (not shown to preserve space) include: gender, age upon arrival at USNA, race/ethnicity, recruited athlete status, prior enlistment status, feeder source, SAT math score, SAT verbal score. All models contain controls for freshman-year GPA, course-section by year fixed effects, as well as a set of binary controls for students' academic majors. Standard errors are clustered by course-section by year groups.

Table 8: Binary Major Choice Models - Peer vs. Grade Effects - Differences Across Semesters

Major choice:	History		Political Science		Chemistry	
Freshman took course in:	Fall (1)	Spring (2)	Fall (3)	Spring (4)	Fall (5)	Spring (6)
Prop(upperclass companymates in major)	**0.130**	**0.241*** **	**-0.0298**	**0.179***	**0.0589**	**0.0700**
	(0.0943)	**(0.0870)**	**(0.107)**	**(0.104)**	**(0.0670)**	**(0.0696)**
Grade for required course in major	**0.0391*** **	**0.0309*** **	**0.0381*** **	**0.0271*** **	**0.0245*** **	**0.0283*** **
	(0.00312)	**(0.00345)**	**(0.00436)**	**(0.00445)**	**(0.00134)**	**(0.00158)**
Additional controls	Y	Y	Y	Y	Y	Y
Academic year FE	Y	Y	Y	Y	Y	Y
Observations	11204	10418	9962	10073	20437	19278
R^2	0.048	0.042	0.046	0.049	0.031	0.038

Major choice:	English		Mathematics	
Freshman took course in:	Fall (7)	Spring (8)	Fall (9)	Spring (10)
Prop(upperclass companymates in major)	**0.0890**	**0.0608**	**0.138***	**0.172** **
	(0.0700)	**(0.0685)**	**(0.0805)**	**(0.0842)**
Grade for required course in major	**0.0203*** **	**0.0186*** **	**0.0180*** **	**0.0180*** **
	(0.00230)	**(0.00232)**	**(0.00145)**	**(0.00147)**
Additional controls	Y	Y	Y	Y
Academic year FE	Y	Y	Y	Y
Observations	19879	19394	14173	13681
R^2	0.058	0.059	0.025	0.025

Note: $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$. Table contains linear probability estimates of the choice of each major (versus any other major) as a function of observable characteristics and (exogenous) proportion of upperclass companymates who chose that major (which captures the reduced form peer effect of the influence of upperclass companymates on major selection), and course grade in the mandatory course in that discipline that all freshmen must take. Regressions are shown only for major choices in which students are exposed to the discipline automatically in their freshman year. Regressions are stratified by "semester groups" to exploit random variation in when they are assigned to take the political science and history courses (for example, column 1 contains freshmen who were assigned American Naval History in the fall semester, whereas column 2 contains those who took it in the spring). Additional controls (not shown to preserve space) include: gender, age upon arrival at USNA, race/ethnicity, recruited athlete status, prior enlistment status, feeder source, SAT math score, SAT verbal score. Standard errors are clustered by academic year by company groups.

Table 9: Binary Major Choice Models - Full Company Effects - Differences Across Shot-gun Eras

Time period:	Shot-guns		No Shot-guns		
Coefficient estimate:	Proportion of upperclass companymates in major				
	Coeff.	Std. Error	Coeff.	Std. Error	Test p-value
Aerospace Engineering	0.0448	(0.0928)	0.0657	(0.0864)	0.87
Chemistry	-0.00852	(0.0947)	0.0382	(0.118)	0.76
Computer Science	0.0810	(0.0906)	0.265**	(0.118)	0.22
Electrical Engineering	0.149	(0.106)	0.151*	(0.0906)	0.99
Economics	0.0604	(0.107)	0.131	(0.0979)	0.62
English	0.0863	(0.111)	0.134	(0.0913)	0.74
History	0.304***	(0.0884)	0.160*	(0.0912)	0.26
Information Technology	0.232**	(0.107)	0.0274	(0.0926)	0.15
Arabic or Chinese	-0.00109	(0.00462)	0.105	(0.111)	0.34
Mathematics	**-0.120**	**(0.0988)**	**0.317****	**(0.127)**	**0.01**
Mechanical Engineering	0.0167	(0.117)	-0.0366	(0.101)	0.73
Naval Architecture	0.0457	(0.0949)	0.162	(0.0990)	0.40
Ocean Engineering	0.335***	(0.122)	0.0969	(0.109)	0.15
Oceanography	0.119	(0.0858)	0.112	(0.102)	0.95
Physics	0.0432	(0.108)	0.135	(0.0962)	0.53
Political Science	0.0257	(0.0992)	0.125	(0.0956)	0.47
Quantitative Economics	0.253*	(0.149)	0.290***	(0.0745)	0.82
Systems Engineering	0.0297	(0.0696)	0.187**	(0.0946)	0.18
Observations:	10413		10744		

Note: $^{*}p < .10,^{**}p < .05,^{***}p < .01$. Table shows binary choice models for majors in which we detect statistically significant peer effects. Table contains linear probability estimates of the choice of each major (versus any other major) as a function of observable characteristics and (exogenous) proportion of upperclass companymates who chose that major (which captures the reduced form peer effect of the influence of upperclass companymates on major selection). Sample is stratified by shot-gun (class years 1998-2006) and post-shot-gun eras (class years 2007-2015). The final column displays p-values from tests of the statistical difference between coefficients across the two subsamples. Additional controls are not shown to preserve space. Standard errors are clustered by academic year by company groups.

Table 10: School-major Choice Models - Differences Across Shot-gun Eras

Choice of major in School:	Engineering		Math and Science		Humanities and Social Sciences	
Era:	Shot-guns	No shot-guns	Shot-guns	No shot-guns	Shot-guns	No shot-guns
Proportion of upperclass	**0.231****	**0.202****	**0.142**	**0.00711**	**0.0552**	**0.103**
companymates in same School-major	**(0.101)**	**(0.0937)**	**(0.104)**	**(0.114)**	**(0.0956)**	**(0.0923)**
Female (binary)	-0.0830***	-0.0747***	0.0966***	0.0899***	-0.00815	0.0000989
	(0.0104)	(0.00987)	(0.0118)	(0.0111)	(0.0125)	(0.0110)
Age (at arrival date)	-0.0203***	-0.00704	-0.0117	-0.00985	0.0254***	0.0175**
	(0.00738)	(0.00753)	(0.00750)	(0.00756)	(0.00731)	(0.00822)
Race/ethnicity (ref.: white)						
Black	-0.0205	-0.0425***	0.0123	-0.0244	-0.0793***	-0.0328*
	(0.0173)	(0.0150)	(0.0197)	(0.0180)	(0.0209)	(0.0196)
Asian	-0.0573***	-0.0294	0.0285	0.0307	0.0270	-0.0139
	(0.0218)	(0.0208)	(0.0227)	(0.0214)	(0.0230)	(0.0197)
Hispanic	-0.0432***	-0.0346***	-0.0145	0.0128	0.0310*	0.00442
	(0.0150)	(0.0131)	(0.0148)	(0.0135)	(0.0180)	(0.0143)
Additional controls	Y	Y	Y	Y	Y	Y
Academic year FE	Y	Y	Y	Y	Y	Y
Observations	10413	10744	10413	10744	10413	10744
R^2	0.107	0.102	0.021	0.018	0.125	0.119

Note: $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$. Linear probability estimates of the choice of majoring within a School at USNA (Engineering, Math and Science, or Humanities and Social Science) versus choosing either of the other two Schools, with samples stratified by shot-gun eras. Choice is modeled as a function of observable characteristics and (exogenous) proportion of upperclass companymates who chose that School (which captures the reduced form peer effect of the influence of upperclass companymates on major selection). Additional controls (not shown to preserve space) include: recruited athlete status, prior enlistment status, feeder source, SAT math score, SAT verbal score. Standard errors are clustered by academic year by company groups.

Table 11: Binary Major Choice Models - Peer vs. Grade Effects - Differences Across Semesters and Shot-gun Eras

Semester:	Fall			Spring		
Time period:	Shot-guns	No Shot-guns		Shot-guns	No Shot-guns	
History			p-value			p-value
Prop. upperclass companymates in major	0.178	0.169	0.96	0.251**	0.247*	0.98
	(0.140)	(0.141)		(0.117)	(0.137)	
Grade for required course in major	0.0417***	0.0378***		0.0340***	0.0260***	
	(0.00468)	(0.00481)		(0.00477)	(0.00541)	
Political Science						
Prop. upperclass companymates in major	-0.144	0.222	0.08	0.299*	0.0564	0.25
	(0.145)	(0.150)		(0.161)	(0.137)	
Grade for required course in major	0.0496***	0.0227***		0.0211***	0.0280***	
	(0.00639)	(0.00621)		(0.00705)	(0.00612)	
Chemistry						
Prop. upperclass companymates in major	-0.00599	0.0456	0.71	0.0620	0.0516	0.94
	(0.0901)	(0.109)		(0.0976)	(0.112)	
Grade for required course in major	0.0253***	0.0237***		0.0291***	0.0303***	
	(0.00195)	(0.00205)		(0.00239)	(0.00238)	
English						
Prop. upperclass companymates in major	0.0627	0.170*	0.48	-0.0178	0.188*	0.16
	(0.116)	(0.0949)		(0.110)	(0.0964)	
Grade for required course in major	0.0193***	0.0194***		0.0148***	0.0203***	
	(0.00387)	(0.00295)		(0.00380)	(0.00304)	
Mathematics						
Prop. upperclass companymates in major	-0.167*	0.328**	0.00	-0.114	0.360***	0.00
	(0.0933)	(0.127)		(0.100)	(0.134)	
Grade for required course in major	0.0165***	0.0199***		0.0160***	0.0194***	
	(0.00203)	(0.00239)		(0.00196)	(0.00247)	

Note: $^{*}p < .10,^{**}p < .05,^{***}p < .01$. Table contains linear probability estimates of the choice of each major (versus any other major) as a function of observable characteristics and (exogenous) proportion of upperclass companymates who chose that major (which captures the reduced form peer effect of the influence of upperclass companymates on major selection), and course grade in the mandatory course in that discipline that all freshmen must take. Regressions are shown only for major choices in which students are exposed to the discipline automatically in their freshman year. Regressions are stratified by "semester groups" to exploit random variation in when they are assigned to take the political science and history courses and also by shot-gun (class years 1998-2006) and post-shot-gun eras (class years 2007-2015). The columns labeled "p-value" display p-values from tests of the statistical difference between peer effect coefficients across the two subsamples. Additional controls are included in the model but not shown to preserve space. Standard errors are clustered by academic year by company groups.

Table 12: Binary Major Choice Models - Peer vs. Grade Effects - With Gender Interactions

Major choice:	History		Political Science		Chemistry		English		Mathematics	
Freshman took course in:	Fall	Spring	Fall	Spring	Fall	Spring	Fall	Spring	Fall	Spring
Prop(MALE upperclass	0.144	0.203*	-0.0168	0.202*	-0.000491	0.0336	0.0343	0.0373	0.176*	0.218**
companymates in major)	(0.114)	(0.106)	(0.121)	(0.121)	(0.0844)	(0.0923)	(0.0822)	(0.0800)	(0.0973)	(0.101)
× female	0.179	0.0274	-0.0476	0.400	0.421	0.388	0.700**	0.552*	-0.0757	-0.0907
	(0.195)	(0.273)	(0.304)	(0.291)	(0.279)	(0.301)	(0.299)	(0.303)	(0.255)	(0.273)
Prop(FEMALE upperclass	-0.0464	0.279	0.0424	-0.0767	-0.0130	-0.0708	0.0971	0.0747	-0.00653	0.0000662
companymates in major)	(0.294)	(0.395)	(0.261)	(0.222)	(0.119)	(0.122)	(0.0949)	(0.0980)	(0.157)	(0.193)
× female	-0.404	1.120	-0.464	-0.191	0.156	0.219	-0.589	-0.657*	0.343	0.483
	(0.545)	(0.735)	(0.672)	(0.520)	(0.387)	(0.409)	(0.377)	(0.385)	(0.465)	(0.511)
Grade for required	0.0411***	0.0332***	0.0386***	0.0267***	0.0188***	0.0226***	0.0166***	0.0182***	0.0147***	0.0146***
course in major	(0.00347)	(0.00383)	(0.00476)	(0.00478)	(0.00138)	(0.00168)	(0.00213)	(0.00219)	(0.00156)	(0.00149)
× female	-0.0101*	-0.0122*	-0.00115	0.00237	0.0279***	0.0304***	0.0198***	0.00183	0.0168***	0.0180***
	(0.00569)	(0.00692)	(0.0104)	(0.0104)	(0.00404)	(0.00480)	(0.00711)	(0.00751)	(0.00420)	(0.00461)
Female (binary)	-0.0138	-0.0181	0.0444	-0.0165	-0.0416***	-0.0435***	0.0103	0.0727***	-0.0212**	-0.0225*
	(0.0217)	(0.0261)	(0.0492)	(0.0502)	(0.00906)	(0.0100)	(0.0271)	(0.0280)	(0.0107)	(0.0118)
Additional controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Academic year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	11203	10389	9933	10073	20411	19257	19849	19364	14152	13660
R^2	0.048	0.043	0.046	0.049	0.036	0.044	0.059	0.060	0.026	0.027

Note: $^*p < .10,^{**} p < .05,^{***} p < .01$. Table contains linear probability estimates of the choice of each major (versus any other major) as a function of observable characteristics and (exogenous) proportion of upperclass companymates who chose that major (which captures the reduced form peer effect of the influence of upperclass companymates on major selection), and course grade in the mandatory course in that discipline that all freshmen must take. Regressions are shown only for major choices in which students are exposed to the discipline automatically in their freshman year. Regressions are stratified by "semester groups" to exploit random variation in when they are assigned to take the political science and history courses (for example, column 1 contains freshmen who were assigned American Naval History in the fall semester, whereas column 2 contains those who took it in the spring). Additional controls (not shown to preserve space) include: age upon arrival at USNA, race/ethnicity, recruited athlete status, prior enlistment status, feeder source, SAT math score, SAT verbal score. Standard errors are clustered by academic year by company groups.

Table 13: Binary Major Choice Models - Peer vs. Grade Effects - With Minority Interactions

Major choice:	History		Political Science		Chemistry		English		Mathematics	
Freshman took course in:	Fall	Spring	Fall	Spring	Fall	Spring	Fall	Spring	Fall	Spring
No. NON-MINORITY upper-	0.00266	0.0000808	0.00200	0.00398	0.000261	-0.000508	-0.000570	-0.00115	0.00105	0.00211
class companymates in major	(0.00221)	(0.00208)	(0.00262)	(0.00279)	(0.00126)	(0.00134)	(0.00143)	(0.00144)	(0.00186)	(0.00195)
× minority	0.00197	0.00512	-0.00128	0.00139	0.00266	0.00395	-0.000603	0.000342	0.0000871	0.000109
	(0.00383)	(0.00362)	(0.00472)	(0.00443)	(0.00308)	(0.00323)	(0.00303)	(0.00312)	(0.00441)	(0.00464)
No. MINORITY upper-	0.00283	0.00483	-0.00493	-0.00193	-0.00198	-0.000995	0.00338	0.00177	0.0000659	0.000797
class companymates in major	(0.00390)	(0.00395)	(0.00398)	(0.00413)	(0.00183)	(0.00186)	(0.00234)	(0.00239)	(0.00235)	(0.00246)
× minority	-0.00531	-0.0126**	0.0111	0.00707	0.00287	-0.0000732	-0.000196	0.00245	0.00457	0.00542
	(0.00702)	(0.00634)	(0.00695)	(0.00792)	(0.00414)	(0.00442)	(0.00469)	(0.00487)	(0.00534)	(0.00559)
Grade for required	0.0369***	0.0302***	0.0372***	0.0229***	0.0213***	0.0232***	0.0187***	0.0178***	0.0161***	0.0171***
course in major	(0.00354)	(0.00405)	(0.00494)	(0.00541)	(0.00146)	(0.00159)	(0.00257)	(0.00263)	(0.00165)	(0.00169)
× minority	0.00976	0.00526	0.00145	0.0148*	0.0128***	0.0208***	0.00617	0.00385	0.00686**	0.00330
	(0.00628)	(0.00614)	(0.00797)	(0.00859)	(0.00348)	(0.00415)	(0.00504)	(0.00485)	(0.00343)	(0.00358)
Minority (binary)	-0.0259	-0.0275	-0.0157	-0.0729*	-0.0156**	-0.0287***	-0.00297	-0.00285	-0.0106	-0.00132
	(0.0230)	(0.0245)	(0.0377)	(0.0378)	(0.00736)	(0.00817)	(0.0173)	(0.0173)	(0.0104)	(0.0107)
Additional controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Academic year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	11203	10389	9933	10073	20411	19257	19849	19364	14152	13660
R^2	0.048	0.043	0.046	0.049	0.036	0.044	0.059	0.060	0.026	0.027

Note: $^{*}p < .10, ^{**} p < .05, ^{***} p < .01$. Table contains linear probability estimates of the choice of each major (versus any other major) as a function of observable characteristics and (exogenous) proportion of upperclass companymates who chose that major (which captures the reduced form peer effect of the influence of upperclass companymates on major selection), and course grade in the mandatory course in that discipline that all freshmen must take. Regressions are shown only for major choices in which students are exposed to the discipline automatically in their freshman year. Regressions are stratified by "semester groups" to exploit random variation in when they are assigned to take the political science and history courses (for example, column 1 contains freshmen who were assigned American Naval History in the fall semester, whereas column 2 contains those who took it in the spring). Additional controls (not shown to preserve space) include: age upon arrival at USNA, race/ethnicity, recruited athlete status, prior enlistment status, feeder source, SAT math score, SAT verbal score. Standard errors are clustered by academic year by company groups.

Table 14: Grade Performance of Herders - Differences Across Shot-gun Eras

	Five percent cutoff					
Subsample:	Sophomores		Juniors		Seniors	
Era:	Shot-guns	No shot-guns	Shot-guns	No shot-guns	Shot-guns	No shot-guns
Dep. Var.: Course Grade	(1)	(2)	(3)	(4)	(5)	(6)
Herder (ref.: otherwise)	**0.0215***	**0.0171**	**0.0174**	**0.0104**	**-0.00654**	**-0.00719**
	(0.0116)	**(0.0106)**	**(0.0125)**	**(0.0108)**	**(0.0127)**	**(0.0102)**
Additional controls	Y	Y	Y	Y	Y	Y
Freshman-year GPA controls	Y	Y	Y	Y	Y	Y
Academic major controls	Y	Y	Y	Y	Y	Y
Course-section by year FE	Y	Y	Y	Y	Y	Y
Observations	88811	97286	79024	90529	65204	88150
R^2	0.367	0.403	0.302	0.329	0.218	0.225
	Ten percent cutoff					
Subsample:	Sophomores		Juniors		Seniors	
Era:	Shot-guns	No shot-guns	Shot-guns	No shot-guns	Shot-guns	No shot-guns
Dep. Var.: Course Grade	(7)	(8)	(9)	(10)	(11)	(12)
Herder (ref.: otherwise)	**0.0112**	**0.0163****	**0.0109**	**0.00643**	**-0.0183***	**-0.00155**
	(0.00836)	**(0.00779)**	**(0.00909)**	**(0.00785)**	**(0.00943)**	**(0.00748)**
Additional controls	Y	Y	Y	Y	Y	Y
Freshman-year GPA controls	Y	Y	Y	Y	Y	Y
Academic major controls	Y	Y	Y	Y	Y	Y
Course-section by year FE	Y	Y	Y	Y	Y	Y
Observations	88811	97286	79024	90529	65204	88150
R^2	0.367	0.403	0.302	0.329	0.218	0.225

Note: $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$. Table contains OLS estimates of equation (2). Each column pairing stratifies the sample by students' class years (after freshman year) and by shot-gun era. The top set of results uses a five percent cutoff rule (see section 5.2), and the bottom set uses a ten percent cutoff. Additional controls (not shown to preserve space) include: gender, age upon arrival at USNA, race/ethnicity, recruited athlete status, prior enlistment status, feeder source, SAT math score, SAT verbal score. All models contain controls for freshman-year GPA, course-section by year fixed effects, as well as a set of binary controls for students' academic majors. Standard errors are clustered by course-section by year groups.

Table 15: Persistence in Herding Behavior

	Shot-gun era			No shot-guns		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Number of majors in company, major, class-year bin					
Lags of dep. variable:						
$t-1$	0.0342	0.0552	-0.0517	0.0936***	0.114***	0.0472*
	(0.0287)	(0.0340)	(0.0491)	(0.0169)	(0.0213)	(0.0266)
$t-2$	-0.127***	-0.171***	-0.0988**	0.00243	-0.0113	0.00431
	(0.0337)	(0.0418)	(0.0496)	(0.0154)	(0.0183)	(0.0261)
$t-3$	0.0543*	0.0407	0.0401	0.0466***	0.0421**	0.0404*
	(0.0301)	(0.0375)	(0.0526)	(0.0145)	(0.0184)	(0.0230)
$t-4$	-0.105**	-0.147**	-0.0339	0.00148	0.00366	-0.00584
	(0.0408)	(0.0577)	(0.0512)	(0.0138)	(0.0171)	(0.0236)
Class-year FE	Y	Y	Y	Y	Y	Y
Company FE	Y	Y	Y	Y	Y	Y
Major FE	Y	Y	Y	Y	Y	Y
Observations	1,418	868	550	3,048	1,767	1,281

Note: $^{*}p < .10,^{**}p < .05,^{***}p < .01$. Table contains OLS estimates of the autoregressive model shown in equation (4). . Lag $t-1$ refers to the size of the "one year ahead" cohort, $t-2$ refers to the size of the "two years ahead" cohort, etc. Column specifications differ by various subsamples: The first three columns employ data from the Classes of 1999-2006, who were subjected to shot-guns; the last three columns employ data from all later graduating classes whose companies were *not* shot-gunned; columns 1 and 4 are estimated using data from all majors; columns 2 and 5 are estimated using data from only those majors where we detected peer effects in major choice (see Tables 4 and 5); columns 3 and 6 are estimated using data from all other majors where we did *not* detect peer effects in major choice. Fixed effects for class-year, company, and major are included in all specifications.