Empirical evidence on the role of social networks in job-search

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Abstract

This paper examines the effect of social connections on the initial employment of university graduates. I use a unique dataset that matches post graduation employment data to information on social connections from facebook.com. I document that social connections are related to initial job placement. Two facebook friends are four times more likely to work for the same employer after graduation than two random students. This relationship does not appear to be merely a spurious correlation – three different strategies to address potential endogeneity all suggest that the relationship is causal. In addition, the number of facebook friends is positively associated with the probability of a job offer at the time of graduation. At the same time, I do not find evidence that the structure or composition of a student's social network affects employment outcomes.

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1. Introduction

Social connections are viewed as an important factor in the job search process. Employers may use referrals to learn about the productivity of workers.[1] Job seekers can use family members and friends to obtain information about vacancies.[2] Job search through social networks can theoretically lead to wage differences of equally productive workers,[3] intergenerational persistence in economic outcomes,[4] and differences in labor market outcomes between different ethnic groups.[5] Information transmission through social connections is especially important at the beginning of a career, when workers are learning about the labor market and build a reputation.[6]

In this paper, I use a unique dataset that links information on the initial employment of university graduates to information on social connections from facebook.com. This allows me to examine whether social connections affect the job search process. In addition, I am able to examine potential consequences and to document the connection between the characteristics of a student's network and her labor market outcomes.

I study undergraduate students who graduated from Texas A&M University between May 2005 and May 2008. I use data from three sources. I use administrative data on student demographic characteristics and academic performance. My second source of information is a survey of graduates that contains information about job offers, the name of the future employer, and the anticipated salary. I match these data to information on social connections from the social networking web-site Facebook.com collected in January 2005. Note that I observe data on social connections prior to the

[1] See Montgomery (1991) and Simon and Warner (1992) for models, and Bewley (1999) for survey evidence.
[2] See Granovetter (1973), Rees (1966), Ioannides and Datcher-Loury (2004) and Pellizzari (Forthcoming) for survey evidence.
[3] Fontaine (2008), Calvo-Armengol and Zenou (2005), Kugler (2002), Calvo-Armengol and Jackson (2004), Turocy and Mayer (2009), and Ioannides and Soetevent (2006).
[4] Calvo-Armengol and Jackson (2009)
[5] Calvo-Armengol and Jackson (2004)
[6] Sacerdote and Marmaros (2002) report that graduating college students perceive networking as an important tool for job search. Students use contacts to peers and alumni to secure good employment opportunities.

realization of employment outcomes. This timing is critical because it allows me to more credibly estimate the effect of (pre-existing) social networks on employment outcomes.

To address the question "Do social networks affect the allocation of workers to jobs?", I construct all possible pairs of students and examine whether socially connected students are more likely to work for the same employer. I find that two facebook friends are four times more likely to work for the same employer after graduation than two random students. This relationship could reflect the impact of social connections on the job search process. However, it is also possible that certain student characteristics affect both the formation of friendships and students' career choices. This can create a spurious relationship between social connections and employment outcomes.

I use three strategies to address this concern. First, I include a rich set of controls for other factors that may influence students' employment outcomes. The effect of facebook friendships on the probability of working for the same employer is reduced only slightly when controlling for a number of student characteristics, such as major, grades, SAT scores, gender, race and parental background.

My second approach to address endogeneity concerns is to focus on students who end up working for a set of very similar employers: Big Oil and Gas extraction corporations, such as Shell, Exxon or Chevron. The decision to work for a particular company within this group is less likely explained by student characteristics that are also related to the formation of social connections. Nevertheless, I find a clear connection between facebook friendships and common employer for students working in this industry.

My third approach to address endogeneity is to impose an exclusion restriction and use a two stage least squares strategy. I assume that the major, college and GPA of students in the fall of 2004 are related to the formation of a facebook friendship by spring 2005, but – conditional on major, college and GPA at graduation – they are not related to the choice of employer. If valid, the instrumental variable approach not only addresses potential endogeneity issues, but it also helps to account for the fact that facebook friendships are only a proxy for the actual social networks of students. Such a noisy measure of social connections could lead to attenuation bias and an understatement of the true effects of social connections. My two stage least squares estimates for the effect of a facebook friendship on common employer are an order of a magnitude higher than the OLS estimates. This suggests that the downward bias due to measurement error is more severe than the upward bias due to the endogeneity of friendship formation. Together, the results of these three approaches suggest that social connections can have an important effect on the job search process.

After I have established that social connections affect the job search process, I examine potential consequences. Social networks form along racial and socioeconomic lines.[7] Therefore, the effects of social networks on the job search process can lead to an association between background characteristics and employment outcomes.[8] However, I am not able to find a connection between common race, parental education or parental income and the probability of working for a common employer. While students are forming social connections along ethnic or socioeconomic lines,[9] social networks formed on the Texas A&M campus do not lead to segregation along these lines in the labor market. Other – potentially random – influences are relatively more important for the formation of relevant social connections. For a less homogeneous group of individuals this may be different. For example, Dustman et al. (2009) analyze German social security data and report a clear association between ethnic background and common employer.

One of the novel features of my data is that I have a direct measure of social connections. I am able to look at a social network at its entirety and examine effects of the composition and structure of an individual's social network on employment outcomes. I find that the number of facebook friends of a student is positively associated with the probability of having a job offer at the time of graduation. This is consistent with greater access to information of more socially active students, but could also be explained by unobserved characteristics that are useful in finding employment and are correlated with

[7] Mayer and Puller (2008), Sacerdote and Marmaros (2006), and Weinberg (2007)
[8] Calvo-Armengol and Jackson (2004, 2009)
[9] Mayer and Puller (2008) document this pattern for these facebook friendships used here. They also point out that friendship formation is not explained by observable characteristics.

the number of facebook friends. In either case my data reveal an effect of soft skills or attributes related to sociability on employment outcomes.

I examine Granovetter's (1973) "strengths of weak ties" hypothesis. He argues that more dispersed social networks with less overlap provide more access to information. I find no statistically significant connection between the clusteredness (a measure of cliquishness) of an individual's network and either the probability of a job offer or salary. Similarly, I find that the ethnic or economic (based on parental background) diversity of students' networks has no effect on the probability of receiving a job offer or on salary. After controlling for student characteristics, I am also not able to find a connection between the characteristics of a student's facebook friends and salary or employment status.

My results contribute to the empirical literature on the effects of social interactions on labor market outcomes.[10] The oldest sources of evidence that social connections matter in the job search process are surveys where workers are asked how they found their current job. At different points in time, for various industries, and in many countries, a large share of workers report that they found their job through social contacts.[11] More recent, direct evidence is based on the connection between residential proximity and employment outcomes,[12] and the connection between ethnic background and common employer.[13] Sacerdote and Marmaros (2002) also examine employment outcomes of college graduates. They report that employment outcomes of randomly assigned dorm-mates at Dartmouth College are correlated. There is very little empirical research on connection between network structure and the job search process. Granovetter provides survey evidence that links the strengths of ties to the usefulness in the job search process. Tassier (2006) uses General Social Survey data and finds

[10] See Ioannides and Datcher-Loury (2004) for a survey.
[11] See Granovetter (1973), Rees (1966), Ioannides and Datcher Loury (2004), Pellizzari (Forthcoming).
[12] Bayer, Topa and Ross (2008) and Hellerstein et al. (2009) show that workers who live in close proximity to each other are more likely to work at the same location (Bayer et al.) or company (Hellerstein et al.). Topa (2001) shows that the relationships between unemployment rates of adjacent neighborhoods suggest a role for social interactions.
[13] Dustmann, et al. (2009) show that in Germany members of the same minority group are more likely to work for the same employer.

evidence supporting Granovetter's "strengths of weak ties" hypothesis. However, he is not able to observe a complete social network of individuals and has to rely on assumptions to construct measures of network structure.

In section 2, I provide on overview over the possible effects of social networks on the job search process and explain which questions I am able to address. In section 3, I discuss my empirical strategy. Section 4 presents the data and Section 5 the results. Section 6 concludes.

2. Social Connections in the Job Search Process

The labor market is characterized by search frictions. Employers and job seekers are not able to observe the existence or attributes of all potential trading partners. They spend time and effort to acquire information about potential trading partners – they search.[14] Social connections can affect the job search process in a number of ways.[15] Job seekers use social connections to obtain information about the existence of vacancies or job attributes.[16] Employers use information from social networks to determine the productivity of potential workers.[17] It is also possible that social connections directly affect preferences to work for a certain employer (e.g. utility is derived from working with friends).

All these mechanisms affect the probability that an individual works for a certain employer. If social connections affect the job search process, socially connected workers are more likely to work for the same employer. If workers are homogeneous and social connections have no effect on the job search process, socially connected workers are not more likely to work for the same employer than workers who are not connected. Consequently, measuring the relationship between social connections and the probability of working for same employer is a common strategy to examine whether social

[14] See Rogerson, Shimer and Wright (2005) for a survey on the labor search literature.
[15] See Jackson (2006) for a survey of the literature of social networks in economics.
[16] This is the most common mechanism in theoretical models of social networks in the labor market. See for example Calvo-Armengol and Jackson (2004,2007), Ioannides and Soetevent (2006), Calvo-Armengol and Zenou (2005), or Fontaine (2008).
[17] See Montgomery (1991) and Bewley (1999).

connections affect the job search process. For example, Bayer, Topa and Ross (2008) and Hellerstein et al. (2009) show that workers who live in close proximity to each other are more likely to work at the same location or company. In this paper I use a similar strategy. To answer the question: *Do social networks affect the allocation of workers to jobs?* I examine the relationship between facebook friendships and the probability of working for the same employer.

Social connections tend to be formed between individuals who share similar characteristics. This preference for interaction with similar individuals is referred to as homophily, and has been documented in both the sociology and economics literature. For example, social connections form along socioeconomic or ethnic lines.[18] Theoretical models of job search with social networks reveal potential consequences of this pattern. These include intergenerational persistence in economic outcomes[19] or differences in employment outcomes between ethnic groups.[20] Social networks manifest themselves through the probability that a worker works for a certain employer. If social connections do in fact lead a connection between ethnic or socioeconomic background and labor market outcomes, members of the same ethnic or socioeconomic group are more likely to work for a common employer.[21] I examine whether this is true and use the results to address the question: *Do the effects of social connections on the job search process lead to socioeconomic / racial segmentation?*

If social connections affect the job search process, the characteristics of an individuals social network can affect labor market outcomes. For example, "better" networks may lead to a higher probability of finding employment. If "better" networks result in more job offers these additional options may lead to a positive relationship between network quality and salary.[22] Alternatively

[18] Mayer and Puller (2008), Sacerdote and Marmaros (2006), and Weinberg (2007)
[19] Calvo-Armengol and Jackson (2009)
[20] Calvo-Armengol and Jackson (2004)
[21] In fact Dustmann et al. (2009) use the relationship between ethnic background and employer establish a role of social connections in the labor market.
[22] Calvo-Armengol and Zenou (2005) , Fontaine (2008), Turocy and Mayer (2010)

reduced uncertainty about the productivity of workers can lead to an association between network quality and starting salaries.[23]

A network can be “better” along a number of dimensions. A bigger network may offer more contacts and hence more information. Consequently, the number of social contacts could be positively related with the probability of finding employment and with the salary of a worker.

Granovetter (1973) emphasizes the usefulness of looser social connections for the job search process - “strengths of weak ties”. He suggests that more dispersed social networks with less overlap provide more access to information than close knit networks where members have similar, redundant sources of information.[24] If Granovetter is correct, individuals with looser social networks, whose members are less well connected among each other, are more likely to find employment and have higher salaries.

A network may also be “better” because it is composed of the “right” kind of individuals who can provide the best information. The consequence would be that individuals with the “right” friends are more likely to find employment and have higher salaries. It is possible that employed friends are the “right” friends. Employed individuals have more access to relevant information. Moreover, in a network with many unemployed individuals there is more competition for information about vacancies. In fact, many theory papers make the assumption that employed worker pass along information about job openings to their friends, while unemployed workers exploit this information and do not pass it along.[25] This means networks with more employed friends or a higher share of employed friends provide more information about job openings. It is also possible that the “right” friends are students in same major who have more relevant information, or students from high income families who are be able to obtain more information from their relatives. If it is indeed advantageous to obtain information from many diverse sources it might be beneficial to have a social network with

[23] Pinkston (2008)
[24] See also Mongtomery (1999) and Tassier (2006).
[25] For example: Calvo-Armengol and Jackson (2004), Ioannides and Soetevent (2007), or Fontaine (2008).

members that differ from each other. In this case the “right” friends are diverse friends. To address the question: “*What kind of social networks are useful in the job search process?*” I investigate the relationship between the structure and composition of social networks and employment outcomes.

3. Empirical Strategy

My measure of social connections are facebook friendships in the January of 2005. My employment outcomes are obtained from students graduating between May 2005 and May 2008.[26] Hence the social connections I observe existed prior to the realization of employment outcomes. Facebook friendships do not capture all relevant social connections of students. Therefore, I view facebook friendships as an imperfect (noisy) measure of the actual social interaction of students.

3.1 Do social networks affect the allocation of workers to jobs?

The most direct evidence of an effect of social networks on the job search process is an effect on the likelihood of working for same employer. To examine whether this is the case, I construct all possible pairs of students. Then, I compare the probability that two facebook friends work for the same employer to the probability that two random students work for the same employer.

The observation that two facebook friends are more likely to work for the same employer than two random students is consistent with an effect of social connections on the job search process. However, it is also possible that students with certain characteristics are more likely to work for a particular employer and that these same common characteristics make it more likely to be socially connected. Equations (1) and (2) illustrate this problem:

$$Friend_{ij} = F\left(\alpha_0 + W_{ij}'\alpha_W + e_{ij} > 0\right) \tag{1}$$

$$Same\_Employer_{ij} = S\left(\beta_0 + \gamma Friend_{ij} + W_{ij}'\beta_W + u_{ij} > 0\right). \tag{2}$$

[26] See Section 4 for a more detailed description of the data.

The indicator variable $Friend_{ij}$ captures whether two students are facebook friends. Equation (1) states that a facebook friendship between students ***i*** and ***j*** depends on their characteristics, W_{ij}, and a random term e_{ij}.[27] Equation (2) expresses the probability that ***i*** and ***j*** work for the same employer as a function of facebook friendship, the student characteristics and a random term u_{ij}. The effect of a friendship between ***i*** and ***j*** and the probability of working for the same employer is captured by the parameter γ. Estimating equation (2) without taking the characteristics, W_{ij}, into account can lead to biased estimates of γ.

I use three strategies to address this concern. First, I include a set of controls intended to capture the characteristics W_{ij}. I am able to observe some of the elements of W_{ij}, I denote these by X_{ij}. Some characteristics are not observable, I denote these by U_{ij}, and $W_{ij} = \left[X_{ij} \quad U_{ij} \right]$. The equation I estimate is:

$$Same\_Employer_{ij} = S\left(\beta_0 + \gamma Friend_{ij} + X_{ij}'\beta_X + v_{ij} > 0\right), \qquad (3)$$

with $v_{ij} = U_{ij}'\beta_U + u_{ij}$. This approach is able to overcome the endogeneity issue if X_{ij} contains the characteristics relevant for both friendship formation and the job search process. If X_{ij} does not contain all the relevant characteristics some bias in the estimates of γ may remain.

My second approach to address endogeneity concerns is to focus on students who end up working for a set of very similar employers: Big Oil and Gas extraction corporations, such as Shell, Exxon or Chevron.[28] If these employers are indeed very similar, students would be largely indifferent between working for a specific employer in this group, and the decision to work particular company is

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[27] The characteristics of a pair of students can be captured by a dummy that captures a common feature, such as same major, or differences between characteristics of the two students, $W_{ij} = abs\left(w_i - w_j\right)$.

[28] I would like to thank John Moroney for helping me to identify this set of companies. They are Anadarko Petroleum, BP, Chevron, Conoco Phillips, Exxon Mobil, Hess and Shell.

not explained by student characteristics that are also related to the formation of social connections. Formally, conditional on working in this industry I assume that either in equation (1) $\alpha_W = 0$, or in equation (3) $\beta_U = 0$. At the same time, social connections still can lead to better chances of employment at (or a preference for) a specific company, i.e. $\gamma > 0$.

My third approach to address endogeneity is to impose an exclusion restriction on the system of equations (4) and (5) and estimate γ using two stage least squares.

$$Friend_{ij} = \alpha_0 + Z_{ij}\alpha_Z + X_{ij}\alpha_X + \varepsilon_{ij} \quad (4)$$

$$Same\_Employer_{ij} = \beta_0 + \gamma Friend_{ij} + X_{ij}'\beta_X + v_{ij} \quad (5)$$

Where X_{ij} is a set of controls including academic information at the time of graduation. A student's major, college or GPA at the time of graduation are related to the choice of employer and are also related to the probability that two students form a friendship. Z_{ij} are controls for the major, college and GPA in the fall semester of 2004. My identifying assumption is that – conditional on X_{ij} – Z_{ij} and v_{ij} are not correlated. I assume that, the major, college and GPA of students in the fall of 2004 is related to the formations of a facebook friendship by Spring 2005 but conditional on major, college and GPA at graduation they are not related to the choice of employer. This assumption is not trivial. To see this, imagine a group of students all graduating with a 3.0 GPA. My assumption states that, within this group, two students with a low GPA in the fall of 2004 are equally likely to work for the same employer, as a student with a low GPA and a student with a high GPA in the fall of 2004. Moreover, friendship formation has a large random component and friendships are hard to predict based on observable characteristics, consequently my instrument will be weak even if the exclusion restriction is valid. Therefore, the results have to be viewed with caution. Nevertheless, they provide an additional piece of information about the potential bias of estimates of γ. If valid, the instrumental variable approach not only addresses potential endogeneity issues that could lead to upward biased estimates of γ, it also helps to account for the fact that social connections that facebook friendships are a noisy measure of social connections, potentially downward biasing the estimates of γ.

3.2 Do social networks lead to socioeconomic / racial segmentation?

I investigate whether social connections can lead to differences in employment outcomes between different socioeconomic or ethnic groups. I do this by examining whether members of the same socioeconomic or ethnic group are more likely to work for the same employer. I estimate:

$$Same\_Employer_{ij} = S\left(\beta_0 + \delta Same\_Group_{ij} + X_{ij}'\beta_X + u_{ij} > 0\right), \qquad (7)$$

where X_{ij} captures characteristics of the student pair ***i / j*** and $Same\_Group_{ij}$ is an indicator that ***i*** and ***j*** are members of the same socioeconomic or ethnic group. A positive estimate for δ is not necessarily the result of the effects of social connections on the job search process and network formation along socioeconomic or ethnic lines. It is possible that members of a group share certain skills or tastes that make it more likely to work for specific employer. Estimating δ provides an upper bound for an effect of the formation of social connections along ethnic or socioeconomic lines on employment outcomes.

3.3 Does the structure / composition of a student's network matter?

To investigate what kind of social networks are most useful in the job search process, I regress students' labor market outcomes on various characteristics of their facebook networks, denoted by $network_i$, and set of student characteristics, X_i. Each observation is an individual student.

$$outcome_i = \beta_0 + \phi network_i + X_i'\beta_X + v_i \qquad (8)$$

I consider two outcomes: salary and employment status at the time of graduation. The network characteristics that I examine are: the number of facebook friends, the cliquishness or dispersion of the friendship network, the diversity of a student's network and the composition of the network in terms of the characteristics of a student's facebook friends.

Size

I investigate whether the size of a student's network is associated with employment outcomes. I estimate equation (8) with the number of facebook friends as the independent variable and either employment status or salary as the dependent variable. There are two alternative explanations for a positive association between the number of friends and employment or salary. First, bigger social networks are better social networks and provide more information useful in the job search process. Second, students with more friends may be more energetic, outgoing, or likeable and these traits might be rewarded in the labor market. I include controls for student characteristics in equation (8). However, it is plausible that these controls are not able to capture hard to measure traits such as likability. Therefore, I am not able to conclusively distinguish between the two explanations.

Structure

The "strength of week ties" hypothesis postulates that more dispersed networks can provide more information to job seekers. To examine this theory I follow a strategy similar to Tassier (2006) and estimate the relationship between the structure of a student's network and her employment outcomes. A measure that captures how closely knit social networks are is the cluster coefficient. It is defined as the fraction of friends of student *i* that are friends with each other:

$$cluster_i = \frac{connections\ between\ friends\ of\ i}{possible\ connections\ between\ friends\ of\ i}$$

I examine the "strength of week tie" hypothesis by including the cluster coefficient as an independent variable in equation (8), together with the number of friends and friends of friends. A smaller cluster coefficient implies less overlap in these friends of friends.

Diversity

I investigate whether there is a relationship between the diversity of a students friendship network and employment outcomes. I use the social segregation index (SSI) proposed by Echenique and Fryer (2007) to measure the diversity of a students network with respect to race and parental income. I estimate (8) with the SSI as an independent variable.

Composition

I examine whether the characteristics of a student's friends are related to her employment outcomes. I include the share of employed friends as an independent variable in equation (8) to examine whether a relationship between the fraction of employed friends and the probability of employment exists. Similarly, I use the share of friends in the same major and the share of friends from high income households as independent variables.

4. Data

I use information from three data sources. I use administrative records of all undergraduate students enrolled at Texas A&M University in the fall of 2004. These records contain demographic background information of the students, such as gender, race, high-school attended, or parental education. They contain information on the life of a student on campus such as membership in sororities / fraternities. Furthermore, the university records provide me with information on students' grade point averages and their majors.

My second source of data is a survey of graduating A&M students conducted by the university career center. My data covers students who graduated between Spring 2005 and Spring 2008. The survey asks students about their plans after graduation. They provide information about plans for graduate school and initial employment. Students who already found employment are asked to provide the name of their employer and their initial annual salary.

My third source of information is the social networking website facebook.com. I have information about all Texas A&M students using facebook in January 2005. In the spring of 2005, Facebook.com was essentially a online directory, limited to university students. To participate on Facebook, students had to sign up using an official university email address, ensuring that they are members of the campus community. Facebook allowed students to set up one profile page which included one picture, name, gender, high school, major, classes taken, music tastes, and other interests, as well as any musings the student wishes to share. Students registered on Facebook were able to browse the profiles of other students at their university. Facebook has been opened to the general public and has added features over time, many of the current features were not available at the time when these data were collected.

The facebook-profiles of the students contain a list of ‘friends’. A Facebook friendship is formed if student A sends a friendship request via the website to student B and student B accepts A’s friendship invitation. Student A appears as a friend on B’s Facebook profile and vice versa. I use these friend connections as a proxy for a student’s social network. Facebook friendships are usually not formed online. The initial interaction between facebook friends is usually face to face. Facebook is a way to communicate.[29] At the time this data was collected the average number of facebook friends at A&M was 42.

[29] Steven Puller and I conducted informal surveys about the nature of Facebook friendships in several undergraduate classes at Texas A&M. The students describe their Facebook friends as acquaintances made at school or social activities. Students say they would be willing to help most of their Facebook friends with a homework assignment. I also can provide slightly more formal evidence that Facebook friendships measure interaction on campus. After this data was collected, Facebook added an additional feature that allows students to self-report how they met each of their friends. Using a sample of this information for Texas A&M, I found that the main channels of meeting friends were being co-members of a school organization (26%), meeting through another friend (16%), attending the same high school (14%), and taking a course together (12%). Very few friendships appear to be merely online interactions (0.4%). The facebook data in this paper were collected in January 2005, and these additional data on meeting channels were collected in July 2006.

Table 1 describes the raw data from these sources. I have information on demographic background and academic performance for the 32070 undergraduates who were enrolled in the fall of 2004. 19701 of the students answered the career center survey at graduation. The observable characteristics of these students are very similar to those in the overall student body. The only exception is that younger cohorts are less likely to have completed the survey. Some of them have not graduated by the spring of 2008 the last date of the survey. 8978 of the students in the overall sample and 5341 of the students in the survey sample were using facebook in the spring of 2005. Facebook is more popular among females and the younger cohorts. Otherwise, the characteristics of the students on facebook are similar to the overall student body. Table 2 focuses on the 4143 students who completed the survey, used facebook and reported to have no plans to attend graduate school. Their characteristics are displayed in Sample A. Sample B consists of the 1988 students who report the name of their future employer in the career center survey (I dropped students who report the military or Texas A&M as their future employer). These 1988 students work for 1144 different companies (see Table A1). 878 employers employ only one student, 121 employers employ two students. The biggest employer is Exxon Mobil, hiring 22 students. Sample C contains the 1670 students who report their salary. Finally, I focus student who are active facebook uses and I display the summary statistics for students with at least 5 facebook friends in sample D. The characteristics of the students in the four samples described in Table 2 are very similar. The only noticeable difference arises from the pattern that female students are less likely to have a job lined up at the time of graduation.

5. Results

First, I examine the association between social connections and the probability of working for the same employer. Then, I investigate the relationship between employment outcomes and the makeup of an individual’s facebook network.

5.1 Facebook Friendship and Common Employer

The most direct manifestation of an effect of social networks on the job search process is a connection between facebook friendships and the probability of working for a common employer. To investigate such a connection I look at pairs of students who report the name of their employer – sample B in Table 2. I construct all possible pairs of the 1988 students who report the name of their employer. The characteristics of these pairs are displayed in Table A2.

I tabulate the pairs of students according to facebook friendship, common major and common employer. Panel a) of Table 3 displays the number of student pairs who are facebook friends and /or have the same major. Panel b) expresses these numbers in terms of shares of all pairs of students. Only 3% of all pairs consist of students with the same major and only 0.5% of all pairs are facebook friends. Panel c) displays the number of student pairs who are facebook friends and / or work for the same employer. Panel d) displays the probably of working for the same employer conditional on facebook friendship and common major. Overall less than 0.2% of all pairs work for the same employer. When conditioning on the same major this probability increases to 1.3%. Friends are about four times more likely to work for the same employer than students who are not facebook friends (.0071 vs .0018). Among students in the same major facebook friends are almost three times more likely to work for the same employer. For pairs of students with different majors a facebook friendship increases the probability of working for the same employer by factor four.

I use linear probability regressions to analyze the relationship between facebook friendships, common employer, and various student characteristics more formally.[30] Table 4 displays the results of a linear probability regression of on indicator of facebook friendship on characteristics of student pairs.[31] It can be seen that student pairs of the same race or in a common major are more likely to

[30] I also estimate probit specifications as robustness checks – see below.
[31] For a more detailed discussion of the relationship between student characteristics and facebook friendships see Mayer and Puller (2008).

form a facebook friendship. A look at the R^2 in the regressions reveals that even with a large number of student characteristics it is hard to predict whether two students are facebook friends. In other words, friendship formation is mostly likely driven by a lot of (potentially random) influences unrelated to observed student characteristics. This suggest that in equation (1) the error term is important and the term $W_{ij}'\alpha_W$ is less important – making it less likely that the association between friendship and common employer is mainly due to characteristics that influence both friendship formation and the choice of employer.

Table 5 displays the results of linear probability regressions with common employer as the dependent variable – equation (3). The independent variables are friendship status and a number of common characteristics for each pair. Column (1) shows the regression of common employer on facebook friendship without additional controls – equivalent to the last column of Panel d) in Table 3. In column (2) I add controls for student demographics and background. These include the difference in SAT score, a dummy for common high-school, and dummies for the racial and gender composition of the pair. The point estimate for the effect of a facebook friendship drops slightly from .0053 to .0048. In column (3) I add controls for campus activities such a indicators for fraternity/sorority membership. I also include a dummy for common major or college and the difference in GPA at graduation and in the fall of 2004. As seen above, common major is clearly associated with the probability of working for the same employer. Common college has a similar effect as it captures pairs with related majors. Overall the coefficient for facebook friendship drops from .0053 without any controls to .0039 with the full set of controls. It remains both statistically and economically significant.

In column (4) I only include pairs of students who graduated at the same time. In column (5) I include pairs of students who graduated at different dates. The point estimate for the effect of a facebook friendship on the probability of working for the same employer is higher for pairs graduating at the same time. This is not consistent with the mechanism that one student follows another to a certain employer. It is consistent with both students having access to the same sources of information transmission, or with a preference of the students to work for the same employer.

I estimate two additional specifications as robustness checks. First, I re-estimate the regressions in Table 5 using a probit specification (Table A3). Second, I account for the fact that the probability of working for the same employer as another student depends on total number of students working for this employer. I re-estimate the regressions in Table 5 with the size adjusted probability of working for the same employer as the dependent variable (Table A4). [32] The results of both robustness checks are very similar to those displayed in Table 5.

To address remaining endogeneity concerns I focus on students who report Oil and Gas extraction companies as future employers.[33] Table 6 repeats the tabulations shown in Table 3 for the 1830 pairs of students who work in this industry. 38 of these pairs consist of facebook friends and 380 of the pairs work for the same employer. Facebook friends are twice as likely to work for the same employer as non-facebook friends. If the students share the same major this ratio is even bigger. In Table 7 I look at this association with the help of a linear probability model.[34] The dependent variable is an indicator for common employer. The independent variables are a dummy for facebook friendship and a number of controls. Column (1) does not include any controls and is equivalent to the last column in panel d) of Table 6. The absolute effect of facebook friendship on the probability of working for the same employer is bigger than when considering all employers. Despite the smaller sample size it is still significant at the 5% level. In columns (2) and (3) I add controls for characteristics of the student pairs. The point estimate for the variable facebook friends drops only slightly and remains significant. The fact that the coefficient for friendship does not change as

[32] To obtain the size adjusted probability of working for a given employer I replace the dummy variable that indicates whether two students work for the same employer by the dummy variable divided by to total number of students hired by this employer multiplied by 100:

$$Same\_employer\_adjusted = \frac{same\_employer}{Total\_\#\_students\_at\_employer} * 100$$

[33] These companies are Anadarko Petroleum, BP, Chevron, Conoco Phillips, Exxon Mobil, Hess and Shell.
[34] See Table A5 for probit estimates with similar results.

additional controls are included supports the assumption that – conditional on working in this industry – either $\alpha_W = 0$ in equation (1) or $\beta_U = 0$ in equation (3).

To address potential endogeneity and measurement error issues I also estimate a two stage least squares specification. I impose the exclusion restriction that the Major, College, GPA and Cohort in the fall of 2004 affect the formation of friendships but do not affect the probability of working for the same employer. Column (1) of Table 8 displays the regression of friendship on controls. It can be seen that all 4 variables related to fall 2004 have a significant effect on the probability of forming a friendship. However, the R^2 reveals that friendships are hard to predict using observable characteristics. Consequently, any instrument for friendship will be relatively weak and sensitive to violations of the exclusion restrictions. In column (2) I report the OLS regression of common employer on friendship and controls. Column (3) of Table 8 displays the 2SLS estimates. The point estimate for the effect of a friendship on the probability of working for the same employer increases more than twentyfold, from .0039 to .0912. If the exclusion restrictions are valid this is consistent with a substantial downward bias due to measurement error in the OLS specification. I also estimate a bivariate probit model (see Table A6). I obtain a higher point estimate for the effect of facebook friendship on common employer than in the single equation probit specification. However, the results are not very precise and the associated p-value is .055. Overall, the results based on my exclusion restriction have to be viewed with caution but they provide a further piece of evidence that the relationship between friendships and common employer is indeed causal.

5.3 Background and Common Employer

I investigate whether the effects of social networks on the job search process and network formation along socioeconomic or ethnic lines lead to differences in labor market outcomes for different socioeconomic or ethnic groups. I examine whether pairs with similar parental socioeconomic background – or same race pairs – are it more likely to work for same employer. I do this by estimating equation (7) for different groups.

Table 9 displays the results of OLS regressions of the size adjusted probability of working for the same employer on categorical variables capturing similarities in parental background and on a number of controls. The independent variables in column (1) are: both students are from a high income household and one student is from a high income household. The omitted category is both students are from low income households. I am not able to find a significant relationship between parental income and the probability of working for the same employer.[35] In column (2) the independent variables are categorical variables for parental education. Again I am not able to detect a relationship between parental education on the probability that two students work for the same employer. In column (3), I simultaneously include information on parental income, parental education and various controls for student characteristics. Again I find no relationship between similarities in parental background and the probability of working for the same employer.

Table 10 displays the results of OLS regressions of the size adjusted probability of working for the same employer on the racial composition of pairs of students. In columns (1) and (2) I consider only pairs with at least one white student. The independent variable in column (1) is a dummy variable indicating that both students of the pair are white. In column (2), I add controls for the characteristics of the pair. The point estimates for "both white" are basically zero and the effect is not significant. In columns (3) and (4) I consider pairs with at least one Hispanic student. The point estimates for "both Hispanic" are very close to zero and not significant. The point estimates for "both Asian" or "both Black" (see columns 5 / 6 and 7 / 8) are bigger than for Whites or Hispanics – still the magnitude is smaller than the effect of "being facebook friends". Given the smaller sample size the estimates are not significant.

[35] Students from high income households tend to work for bigger employers. Therefore, using a the dummy variable "common employer" as the dependent variable leads to a statistically – but not economically – significant relationship between parental income and common employer.

Overall, I cannot find evidence that either similar socioeconomic background or common race lead to a meaningful increase in the probability of working for the same employer. However, due to the smaller sample size, I cannot rule out that Asian students or African American students are more likely to work with same race students than with students of a different race.

5.4 Individual Level Results

Now, I examine the connection between the characteristics of an individual's social network and employment outcomes. I estimate various specifications of equation (8). To be able to calculate characteristics of a network and to exclude students who are not active on facebook I restrict the sample to students with at least 5 facebook friends (Sample D in Table 2).

5.4.1 Size of Facebook Network

First, I document the relationship between the number of facebook friendships and employment outcomes. Table 11 shows the results for regressions of the number of facebook friends on student characteristics. It can be seen that students with more educated parents and students from higher income households tend have more facebook friends. This is also true for female students. It is possible that these students are more popular, socially active, or that they are simply more active users of facebook.

Table 12 displays the relationship between having secured employment at the time of graduation and the characteristics of students. In column (1) I show the results of a linear probability regression of a job offer at the time of graduation on student characteristics. Female students are less likely to have secured employment, while a higher GPA is associated with a higher probability of employment. In column (2) the independent variable is the number of facebook friends of a student. Students with more facebook friends are more likely to have found a job at the time of graduation. In column (4) the dependent variables are the number of facebook friends and controls for student characteristics. The point estimate for the effect of one more facebook friendship on the probability of having secured employment drops from .0021 to .0013. This association is still economically meaningful. Twenty additional facebook friends (about one standard deviation) are associated with a similar increase in the probability of employment as a .32 point increase in GPA. It is possible that this is a reflection of the benefit of a big social network in the job search process. It is also possible that students with certain characteristics have more friends and that these same characteristics make it more likely to have found employment by the time of graduation. I include a set of controls but I am not able to capture hard to measure traits such as likability. Therefore, I am not able to conclusively distinguish between the two explanations.

Columns (1), (2), and (4) of Table 13 report the equivalent results with log salary as the dependent variable. Even after including various controls female students have lower starting salaries, while a higher GPA increases the staring salary. The raw correlation between number of facebook friends and salary is basically zero (the point estimate is slightly negative). Students with many facebook friends tend to have characteristics that are associated with lower starting salaries. After adding controls for student characteristics more facebook friends are associated with a higher salary. Again, the positive association between the number of facebook friends and salary is consistent with benefits of a bigger network in the job search process but also with the pattern that characteristics that are associated with a high number of facebook friends also lead to higher wages.

5.4.2 Clusteredness / Diversity of the Social Network

In Column (3) of Table 12, I report the results of a linear probability regression of employment at the time of graduation on the number of facebook friends, the number of friends of friends and the cluster coefficient. If more spread out networks are more useful to obtain information about employment opportunities we would expect to see a negative effect of the cluster coefficient. The point estimate without any controls for student characteristics is positive but not statistically significant. After adding controls in column (5) it is negative and not statistically significant. The estimates with salary as the dependent variable have the opposite sign – columns (3) and (5) of Table 13; but are also not statistically significant. While I cannot reject the null that the cluster coefficient is unrelated to either outcome, it is also not possible to rule out that there is an effect of the network structure. Due the relatively high standard errors the confidence interval for the effect of the cluster coefficient contains economically meaningful effects.[36]

To measure the diversity of an individual's social network I calculate the Spectral Segregation Index (SSI)[37] of each student's facebook network for race and parental income. As reported in columns (3) through (5) in Tables 14 and 15 I find no significant association between either SSI measure and employment status or salary.

5.4.3 Friend Characteristics

In Table 14, I report the relationship between the probability of being employed at the time of graduation and the characteristics of a student's friends. In Column (1) I regress employment status on the fraction of friends who are in the same major, are from high income households and have a job offer at the time of graduation. I do not include other controls. A high share of friends from the same major and a high share of employed friends increase the probability that a student is employed herself. After adding controls for the number of friends and student characteristics these coefficients drop and are no longer significant.[38] While there is an association between the characteristics of a student's facebook friends employment at the time of graduation, it can be largely explained by student characteristics that drive both friendship formation and employment outcomes. A similar picture arises in Table 15 where I consider salary as the dependent variable. Without controls the mean salary

[36] The standard deviation for the cluster coefficient is .08
[37] See Echinique and Fryer (2007).
[38] Including the different friend characteristics one at a time leads similar results.

of a student's facebook friends is clearly associated with her own salary. This relationship is no longer statistically significant once controls for student characteristics are added.

In general, after including controls for student characteristics I am not able to detect a statistically significant relationship between the characteristics of facebook friends and salary or employment status.

6. Conclusion

I use a unique data set that links information on the initial employment of university graduates to facebook friendships formed prior to graduation. To my knowledge this is the first data set that contains a direct measure of social interactions and employment outcomes. I find a strong association between facebook friendship and the probability of working for the same employer. I use three different strategies to address endogeneity concerns. My results suggest that the connection between social interactions and choice of employer is in part causal. Another result that reveals a role for social interactions – or soft skills related to them – in the job search process is that a higher number facebook friends is positively associated with the likelihood of having secured employment at graduation.

This and other recent papers confirm that social connections play an important role in the job search process. However, we still don't fully understand how social connections affect the job search process. The presence of search or matching frictions is one explanation. Students and/or employers may use information from social contacts to reduce these frictions. The use of information from social connections could lead to a more efficient allocation of workers to jobs and increase productivity. An alternative explanation is that individuals derive utility from working with friends and select their employer based on these preferences.

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Table 1
Descriptive Statistics
Students Enrolled Fall Semester 2004

	All		In Survey		On Facebook		In Survey and on Facebook	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Female	0.50	0.50	0.52	0.50	0.55	0.50	0.59	0.49
Black	0.02	0.15	0.02	0.14	0.02	0.14	0.01	0.12
Hispanic	0.10	0.31	0.09	0.29	0.11	0.31	0.09	0.29
Asian	0.04	0.20	0.04	0.19	0.04	0.20	0.03	0.18
White	0.82	0.38	0.84	0.37	0.83	0.38	0.85	0.36
Father College	0.60	0.49	0.61	0.49	0.65	0.48	0.66	0.47
Mother College	0.52	0.50	0.54	0.50	0.56	0.50	0.58	0.49
HH inc>80K	0.49	0.50	0.51	0.50	0.56	0.50	0.58	0.49
F04Fresh	0.18	0.38	0.09	0.29	0.24	0.42	0.13	0.34
F04YrSoph	0.21	0.41	0.21	0.41	0.26	0.44	0.28	0.45
F04YrJr	0.27	0.44	0.32	0.46	0.26	0.44	0.33	0.47
F04YrSr	0.34	0.48	0.38	0.49	0.24	0.43	0.26	0.44
SAT_total	1150	150	1152	148	1168	145	1170	143
FIGPR_Cum	2.95	0.59	3.08	0.48	2.97	0.60	3.12	0.47
Greek	0.13	0.34	0.13	0.34	0.16	0.37	0.17	0.38
Corps	0.01	0.12	0.01	0.10	0.01	0.11	0.01	0.10
Grad school			0.20	0.40			0.22	0.42
In Survey	0.61	0.49	1.00	0.00	0.59	0.49	1.00	0.00
Observations	32070		19701		8978		5341	

Table 2
Descriptive Statistics - Samples
Students Enrolled Fall Semester 2004
In Survey and on Facebook, no plans for gradute-school

	Sample A All Students		**Sample B** Employer Reported		**Sample C** Salary Reported		**Sample D** At Least 5 FB	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Female	0.58	0.49	0.52	0.50	0.46	0.50	0.59	0.49
Black	0.02	0.12	0.01	0.12	0.01	0.11	0.01	0.11
Hispanic	0.09	0.29	0.08	0.27	0.08	0.27	0.09	0.29
Asian	0.03	0.18	0.03	0.18	0.03	0.18	0.03	0.17
White	0.85	0.36	0.87	0.33	0.87	0.34	0.86	0.34
Father College	0.65	0.48	0.67	0.47	0.67	0.47	0.66	0.48
Mother College	0.56	0.50	0.57	0.49	0.58	0.49	0.56	0.50
HH inc>80K	0.57	0.50	0.60	0.49	0.60	0.49	0.59	0.49
F04Fresh	0.13	0.34	0.13	0.34	0.12	0.33	0.13	0.34
F04YrSoph	0.28	0.45	0.28	0.45	0.27	0.45	0.29	0.45
F04YrJr	0.33	0.47	0.32	0.47	0.33	0.47	0.34	0.47
F04YrSr	0.26	0.44	0.26	0.44	0.27	0.45	0.24	0.43
SAT_total	1155	141	1168	140	1176	140	1159	139
FIGPR_Cum	3.04	0.46	3.12	0.44	3.11	0.43	3.06	0.46
greek	0.17	0.38	0.18	0.38	0.17	0.38	0.19	0.39
corps	0.01	0.10	0.01	0.07	0.01	0.11	0.01	0.11
got_job	0.67	0.47	1.00	0.00	1.00	0.00	0.68	0.47
Job_salary					45715	12456	45792*	12464
Observations	4143		1988		1670		3303	

* 1349 Observations

Table 3

Common Employer by Major and Friendship

Pairs of Students

a) Frequency Friendship / Same Major

	Different Major	Same Major	Total
Not friends	1902308	63,584	1965892
Friends	8,266	920	9,186
Total	1910574	64,504	**1975078**

b) Fraction of all pairs

	Different Major	Same Major	Total
Not friends	0.9632	0.0322	0.9953
Friends	0.0042	0.0005	0.0047
Total	0.9673	0.0327	**1.0000**

c) Frequency Friendship / Same Employer

	Different Employer	Same Employer	Total
Not friends	1962336	3556	1965892
Friends	9121	65	9186
Total	1971457	3621	**1975078**

d) Probability of Same Employer

	Different Major	Same Major	Total
Not friends	0.001	0.013	0.002
Friends	0.004	0.033	0.007
Total	0.001	0.013	**0.002**

Table 4
Student Characteristics and Facebook Friendship
Linear Probability Model

Dependent Variable: Facebook Friendship

	(1)	(2)	(3)
Both female	0.00180	0.00122	0.00111
	(0.00014)**	(0.00014)**	(0.00014)**
One female	-0.00003	0.00013	0.00014
	(0.00012)	(0.00012)	(0.00012)
Both Black	0.08349	0.08334	0.08352
	(0.01515)**	(0.01511)**	(0.01511)**
Both Hispanic	0.00123	0.00147	0.00150
	(0.00070)	(0.00069)*	(0.00069)*
Both Asian	0.02058	0.02039	0.02022
	(0.00350)**	(0.00346)**	(0.00346)**
White Black	-0.00085	-0.00008	-0.00000
	(0.00030)**	(0.00029)	(0.00029)
White Hispanic	-0.00157	-0.00110	-0.00107
	(0.00012)**	(0.00012)**	(0.00012)**
White Asian	-0.00128	-0.00080	-0.00084
	(0.00019)**	(0.00019)**	(0.00019)**
Hispanic Black	0.00106	0.00186	0.00201
	(0.00118)	(0.00113)	(0.00113)
Hispanic Asian	-0.00208	-0.00128	-0.00127
	(0.00052)**	(0.00052)*	(0.00052)*
Black Asian	0.00100	0.00172	0.00172
	(0.00183)	(0.00177)	(0.00177)
Other combination	0.00121	0.00100	0.00117
	(0.00065)	(0.00064)	(0.00064)
Absolute difference in SAT		-0.00000	-0.00000
		(0.00000)**	(0.00000)**
Cohort difference Fall 04		-0.00217	-0.00159
		(0.00005)**	(0.00006)**
Fall 04 GPA difference		-0.00071	-0.00049
		(0.00010)**	(0.00013)**
Both Fathers college		0.00054	0.00058
		(0.00016)**	(0.00016)**
One Father college		-0.00009	-0.00007
		(0.00015)	(0.00015)
Both Mothers college		0.00080	0.00079
		(0.00014)**	(0.00014)**
One Mother college		0.00027	0.00027
		(0.00012)*	(0.00012)*
Both athlete		0.05534	0.05532
		(0.00751)**	(0.00751)**
Both crops		0.10570	0.10585
		(0.04187)*	(0.04187)*
Both greek		0.02186	0.02182
		(0.00064)**	(0.00064)**
One_athlete		-0.00024	-0.00020
		(0.00022)	(0.00022)
One crops		0.00339	0.00344
		(0.00057)**	(0.00057)**
One greek		-0.00083	-0.00083
		(0.00010)**	(0.00010)**
Both high income parents		0.00034	0.00029
		(0.00015)*	(0.00015)
One high income parents		-0.00019	-0.00021
		(0.00013)	(0.00013)
Same fall 04 college		0.00204	0.00060
		(0.00016)**	(0.00022)**
Same fall 04 major		0.00858	0.00699
		(0.00053)**	(0.00051)**
Same High School		0.19785	0.19783
		(0.00511)**	(0.00511)**
Cohort difference graduation			-0.00037
			(0.00002)**
Final_GPA difference			-0.00027
			(0.00016)
Same final college			0.00134
			(0.00021)**
Same final major			0.00496
			(0.00046)**
Constant	0.00445	0.00564	0.00609
	(0.00010)**	(0.00021)**	(0.00022)**
Observations	1975078	1975078	1975078
R-squared	0.00060	0.03271	0.03302

Robust standard errors in parentheses
* significant at 5% level; ** significant at 1% level

Table 5
Facebook Friendship and Same Employer
Linear Probability Model

Dependent Variable: Same Employer

	(1)	(2)	(3)	(4)	(5)
Friends	**0.00527**	**0.00489**	**0.00385**	**0.00504**	**0.00330**
	(0.00088)**	**(0.00088)****	**(0.00087)****	**(0.00217)***	**(0.00093)****
Absolute difference in SAT		-0.00000	-0.00000	-0.00000	-0.00000
		(0.00000)**	(0.00000)*	(0.00000)	(0.00000)
Both Female		0.00052	0.00071	0.00127	0.00062
		(0.00009)**	(0.00009)**	(0.00030)**	(0.00010)**
One Female		-0.00037	0.00008	0.00041	0.00003
		(0.00007)**	(0.00008)	(0.00023)	(0.00008)
Same High School		0.00217	0.00227	0.00755	0.00146
		(0.00090)*	(0.00090)*	(0.00371)*	(0.00086)
Cohort difference F04			-0.00005	-0.00019	-0.00005
			(0.00004)	(0.00015)	(0.00004)
F04 GPA difference			0.00009	-0.00008	0.00011
			(0.00010)	(0.00027)	(0.00010)
Final GPA difference			-0.00090	-0.00123	-0.00084
			(0.00010)**	(0.00031)**	(0.00011)**
Same F04 College			0.00122	0.00211	0.00114
			(0.00018)**	(0.00053)**	(0.00019)**
Same F04 Major			0.00008	-0.00113	0.00014
			(0.00038)	(0.00085)	(0.00043)
Same Final College			0.00221	0.00271	0.00211
			(0.00015)**	(0.00043)**	(0.00017)**
Same Final Major			0.00891	0.01064	0.00866
			(0.00047)**	(0.00134)**	(0.00050)**
Controls for Parental Education and Income	No	Yes	Yes	Yes	Yes
Controls for Race	No	Yes	Yes	Yes	Yes
Controls for Campus Activities	No	No	Yes	Yes	Yes
Constant	0.00181	0.00149	0.00085	0.00108	0.00070
	(0.00003)**	(0.00013)**	(0.00014)**	(0.00045)*	(0.00015)**
				Graduated at same time	Graduated at different time
Observations	1975078	1975078	1975078	261487	1713591
R-squared	0.00007	0.00023	0.00328	0.00453	0.00309

Robust standard errors in parentheses
* significant at 5% level; ** significant at 1% level

Note:
Controls for parental education and income are:
Both Fathers College, One Father College, Both Mothers College, One Mother College, Both HH Income above 80k, One HH income above 80k.
Controls for Race are:
Both Black, Both Hispanic, Both Asian, White-Hispanic, White-Asian, White-Black, Hispanic-Black, Hispanic-Asian, Black-Asian, combinations involving other race.
Controls for Campus Activities are:
Both in Sorority/Fraternity, One in Sorority/Fraternity, Both in Corps of Cadets, One in Corps of Cadets, Both Athlete, One Athlete

Table 6
Friendship and Common Employer in Oli/Gas Extraction Industry
Pairs of Students

a) Frequency Friendship / Same Major

	Different Major	Same Major	Total
Not friends	1601	191	1792
Friends	21	17	38
Total	1622	208	**1830**

b) Fraction of all pairs

	Different Major	Same Major	Total
Not friends	0.875	0.104	0.979
Friends	0.011	0.009	0.021
Total	0.886	0.114	**1.000**

c) Frequency Friendship / Same Employer

	Different Employer	Same Employer	Total
Not friends	1427	365	1792
Friends	23	15	38
Total	1450	380	**1830**

d) Probability of Same Employer

	Different Major	Same Major	Total
Not friends	0.204	0.204	0.204
Friends	0.286	0.529	0.395
Total	0.205	0.231	**0.208**

Table 7
Facebook Friendship and Same Employer in Oil/Gas Extraction Industry
Linear Probability Model

Dependent Variable: Same Employer

	(1)	(2)	(3)
Friends	0.19105	0.19270	0.16846
	(0.07991)*	(0.08319)*	(0.08272)*
Cohort difference Graduation		-0.00658	-0.00772
		(0.00463)	(0.00523)
Absolute difference in SAT		0.00012	0.00013
		(0.00008)	(0.00008)
Both Female		-0.04550	-0.03064
		(0.02827)	(0.02945)
One Female		-0.04207	-0.03660
		(0.02388)	(0.02405)
Same High School		0.07022	0.08046
		(0.11185)	(0.10923)
Final GPA difference			-0.03653
			(0.05123)
Same Final College			-0.04132
			(0.05586)
Same Final Major			-0.08238
			(0.03892)*
Cohort difference F04			0.01219
			(0.01464)
F04 GPA difference			-0.02825
			(0.03906)
Same F04 College			0.13198
			(0.05629)*
Same F04 Major			0.07031
			(0.04564)
Controls for Parental Education and Income	No	Yes	Yes
Controls for Race	No	Yes	Yes
Controls for Campus Activities	No	No	Yes
Constant	0.20368	0.22320	0.22330
	(0.00952)**	(0.06006)**	(0.06385)**
Observations	1830	1830	1830
R-squared	0.00451	0.01767	0.03620

Robust standard errors in parentheses
* significant at 5% level; ** significant at 1% level

Note:
Employers are:
Anadarko Petroleum, BP, Chevron, Conoco Phillips, Exxon Mobil, Hess Corp and Shell
Controls for parental education and income are:
Both Fathers College, One Father College, Both Mothers College, One Mother College, Both HH Income above 80k, One HH income above 80k.
Controls for Race are:
Both Black, Both Hispanic, Both Asian, White-Hispanic, White-Asian, White-Black, Hispanic-Black, Hispanic-Asian, Black-Asian, combinations involving other race.
Controls for Campus Activities are:
Both in Sorority/Fraternity, One in Sorority/Fraternity, Both in Corps of Cadets, One in Corps of Cadets, Both Athlete, One Athlete

Table 8
Facebook Friendship and Same Employer
2SLS - Linear Probability Model

Dependent Variable	Friendship	Same Employer	Same Employer
	OLS	**OLS**	**IV**
	(1)	**(2)**	**(3)**
Friends		0.00390	0.09116
		(0.00087)**	(0.02744)**
Both Female	0.00111	0.00066	0.00057
	(0.00014)**	(0.00009)**	(0.00010)**
One Female	0.00014	0.00004	0.00003
	(0.00012)	(0.00007)	(0.00008)
Absolute difference in SAT	-0.00000	-0.00000	-0.00000
	(0.00000)**	(0.00000)*	(0.00000)
Same High School	0.19783	0.00226	-0.01501
	(0.00511)**	(0.00090)*	(0.00554)**
Same F04 College	0.00060		
	(0.00022)**		
Same F04 Major	0.00699		
	(0.00051)**		
F04 GPA difference	-0.00049		
	(0.00013)**		
Cohort difference F04	-0.00159		
	(0.00006)**		
Same Final College	0.00134	0.00307	0.00288
	(0.00021)**	(0.00012)**	(0.00013)**
Same Final Major	0.00496	0.00893	0.00830
	(0.00046)**	(0.00046)**	(0.00049)**
Final GPA difference	-0.00027	-0.00082	-0.00077
	(0.00016)	(0.00007)**	(0.00008)**
Cohort difference Graduation	-0.00037	-0.00005	0.00002
	(0.00002)**	(0.00001)**	(0.00002)
Controls for Parental Education and Income	Yes	Yes	Yes
Controls for Race	Yes	Yes	Yes
Controls for Campus Activities	Yes	Yes	Yes
Constant	0.00609	0.00092	0.00043
	(0.00022)**	(0.00014)**	(0.00020)*
Observations	1975078	1975078	1975078
R-squared	0.03302	0.00323	
F- statistic			50.68

Robust standard errors in parentheses
* significant at 5% level; ** significant at 1% level

Note:
Controls for parental education and income are:
Both Fathers College, One Father College, Both Mothers College, One Mother College, Both HH Income above 80k, One HH income above 80k.
Controls for Race are:
Both Black, Both Hispanic, Both Asian, White-Hispanic, White-Asian, White-Black, Hispanic-Black, Hispanic-Asian, Black-Asian, combinations involving other race.
Controls for Campus Activities are:
Both in Sorority/Fraternity, One in Sorority/Fraternity, Both in Corps of Cadets, One in Corps of Cadets, Both Athlete, One Athlete

Table 9
Parental Background and Common Employer
OLS Regressions

Dependent Variable	Same Employer Size Adjusted	Same Employer Size Adjusted	Same Employer Size Adjusted
	(1)	**(2)**	**(3)**
Both High Parental Income	0.00182		-0.00126
	(0.00222)		(0.00235)
One High Parental Income	0.00095		-0.00016
	(0.00213)		(0.00220)
Both Father College		0.00330	0.00140
		(0.00263)	(0.00278)
One Father College		0.00192	0.00143
		(0.00256)	(0.00265)
Both Mother College		0.00211	0.00233
		(0.00217)	(0.00217)
One Mother College		0.00233	0.00273
		(0.00198)	(0.00198)
Controls	NO	NO	YES
Constant	0.02699	0.02395	0.02593
	(0.00184)**	(0.00259)**	(0.00374)**
Observations	1975078	1975078	1975078
R-squared	0.00000	0.00000	0.00194

Robust standard errors in parentheses
* significant at 5% level; ** significant at 1% level

Note:
Controls are: Both female, One female, Both Black, Both Hispanic, Both Asian, White-Hispanic, White-Asian, White-Black, Hispanic-Black, Hispanic-Asian, Black-Asian, combinations involving other race, Both in Sorority/Fraternity, One in Sorority/Fraternity, Both in Corps of Cadets, One in Corps of Cadets, Both Athlete, One Athlete, Difference in Fall04 cohort, difference in graduation cohort, Same Major Fall04, Same College Fall04, Same Final Major, Same Final College, GPA difference Fall04, Final GPA difference, SAT difference, Same High school.

Table 10
Common Race and Common Employer
Adjusted for Size of Employer

Dependent Variable: Same Employer size adjusted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pairs with at least one White Student		**Pairs with at least one Hispanic Student**		**Pairs with at least one Asian Student**		**Pairs with at least one African American Student**	
Both White	-0.00001	-0.00099						
	(0.00172)	(0.00183)						
Both Hispanic			-0.00507	-0.00686				
			(0.00512)	(0.00864)				
Both Asian					0.04712	0.03973		
					(0.03239)	(0.02286)		
Both Black							0.01789	0.02736
							(0.04764)	(0.05744)
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Constant	0.02807	0.02654	0.02829	0.02758	0.02839	0.03652	0.02959	-0.01729
	(0.00148)**	(0.00383)**	(0.00177)**	(0.00712)**	(0.00288)**	(0.01300)**	(0.00465)**	(0.01983)
Observations	1942693	1942693	299713	299713	125152	125152	53298	53298
R-squared	0.00000	0.00191	0.00000	0.00189	0.00003	0.00392	0.00000	0.00226

Robust standard errors in parentheses
* significant at 5% level; ** significant at 1% level

Note:
Controls are: Both female, One female, Both Fathers College, One Father College, Both Mothers College, One Mother College, Both HH Income above 80k, One HH income above 80k, Both in Sorority/Fraternity, One in Sorority/Fraternity, Both in Corps of Cadets, One in Corps of Cadets, Both Athlete, One Athlete, Difference in Fall04 cohort, difference in graduation cohort, Same Major Fall04, Same College Fall04, Same Final Major, Same Final College, GPA difference Fall04, Final GPA difference, SAT difference, Same High school.

Table 11
Student Characteristics and Number of Facebook Friends

Dependent Variable: Number of Friends

	(1)	(2)
Female	3.0985	2.2230
	(0.7395)**	(0.9017)*
Hispanic	-0.5019	0.7990
	(1.2439)	(1.3076)
Asian	0.8184	1.0746
	(2.1302)	(2.1189)
Black	4.6454	5.0024
	(3.9063)	(3.9961)
Other Race	-2.1696	-1.1386
	(4.8379)	(5.2949)
Father College	4.5136	4.0084
	(0.9893)**	(1.0199)**
Mother College	2.8301	2.7362
	(1.0359)**	(1.0572)**
HH income above 80	2.8448	2.1531
	(0.7493)**	(0.7558)**
Cumulative GPR		0.6213
		(0.9424)
SAT Total		0.0054
		(0.0031)
Controls for Major	No	Yes
Controls for cohort and Graduation Date	Yes	Yes
Constant	10.8771	-2.2833
	(2.9669)**	(4.7653)
Observations	3303	3303
R-squared	0.0397	0.1034

Robust standard errors in parentheses
* significant at 5%; ** significant at 1%

Table 12
Network Size / Structure and Employment at Time of Graduation

Dependent Variable: Employment offer at time of graduation

	(1)	(2)	(3)	(4)	(5)
Friends		**0.0021**	**0.0020**	**0.0013**	**0.0027**
		(0.0004)**	**(0.0014)**	**(0.0004)****	**(0.0013)***
Friends of Friends			**0.0000**		**-0.0000**
			(0.0000)		**(0.0000)**
Cluster Coefficient			**0.0010**		**-0.0398**
			(0.1281)		**(0.1204)**
Female	-0.0561			-0.0590	-0.0582
	(0.0172)**			(0.0172)**	(0.0173)**
Hispanic	0.0000			-0.0010	-0.0023
	(0.0268)			(0.0268)	(0.0269)
Asian	-0.0571			-0.0585	-0.0605
	(0.0436)			(0.0436)	(0.0436)
Black	0.0615			0.0549	0.0515
	(0.0593)			(0.0589)	(0.0590)
Other Race	-0.1266			-0.1251	-0.1260
	(0.1035)			(0.1044)	(0.1056)
Father College	0.0074			0.0021	0.0023
	(0.0245)			(0.0245)	(0.0245)
Mother College	0.0395			0.0359	0.0364
	(0.0235)			(0.0234)	(0.0234)
HH income above 80	0.0140			0.0112	0.0117
	(0.0160)			(0.0159)	(0.0159)
Cumulative GPR	0.0779			0.0771	0.0784
	(0.0198)**			(0.0198)**	(0.0199)**
SAT Total	-0.0001			-0.0002	-0.0002
	(0.0001)*			(0.0001)*	(0.0001)*
Controls for Major	Yes	No	No	Yes	Yes
Controls for Cohort and Graduation Date	Yes	No	No	Yes	Yes
Constant	0.5692	0.6262	0.6266	0.5722	0.5656
	(0.1015)**	(0.0132)**	(0.0168)**	(0.1014)**	(0.1017)**
Observations	3303	3303	3303	3303	3303
R-squared	0.2305	0.0091	0.0091	0.2337	0.2340

Robust standard errors in parentheses
* significant at 5%; ** significant at 1%

Table 13
Network Size / Structure and Anticipated Salary

Dependent Variable: Natural Log of Anticipated Salary

	(1)	(2)	(3)	(4)	(5)
Friends		**-0.0003**	**0.0012**	**0.0007**	**0.0002**
		(0.0003)	**(0.0013)**	**(0.0003)***	**(0.0010)**
Friends of Friends			**-0.0000**		**0.0000**
			(0.0000)		**(0.0000)**
Cluster Coefficient			**-0.0160**		**0.0155**
			(0.1285)		**(0.1052)**
Female	-0.0533			-0.0551	-0.0553
	(0.0156)**			(0.0156)**	(0.0161)**
Hispanic	0.0257			0.0264	0.0267
	(0.0206)			(0.0207)	(0.0208)
Asian	-0.1396			-0.1378	-0.1378
	(0.0959)			(0.0959)	(0.0964)
Black	0.0557			0.0502	0.0518
	(0.0391)			(0.0389)	(0.0389)
Other Race	-0.0423			-0.0408	-0.0412
	(0.0361)			(0.0317)	(0.0310)
Father College	-0.0138			-0.0174	-0.0174
	(0.0212)			(0.0213)	(0.0213)
Mother College	0.0052			0.0037	0.0032
	(0.0220)			(0.0221)	(0.0222)
HH income above 80	0.0245			0.0226	0.0223
	(0.0142)			(0.0141)	(0.0142)
Cumulative GPR	0.0682			0.0677	0.0667
	(0.0161)**			(0.0161)**	(0.0160)**
SAT Total	-0.0001			-0.0001	-0.0001
	(0.0001)*			(0.0001)*	(0.0001)*
Controls for Major	Yes	No	No	Yes	Yes
Controls for Cohort and Graduation Date	Yes	No	No	Yes	Yes
Constant	10.5450	10.6989	10.6918	10.5458	10.5482
	(0.0929)**	(0.0141)**	(0.0193)**	(0.0925)**	(0.0934)**
Observations	1349	1349	1349	1349	1349
R-squared	0.4721	0.0004	0.0014	0.4743	0.4744

Robust standard errors in parentheses
* significant at 5%; ** significant at 1%

Table 14
Network Composition and Employment at Time of Graduation

Dependent Variable: Employment offer at time of graduation

	(1)	(2)	(3)	(4)	(5)
Friends		**0.0013**	**0.0013**	**0.0013**	**0.0010**
		(0.0004)**	**(0.0004)****	**(0.0004)****	**(0.0013)**
Fraction Friends Same Major	**0.2815**	**0.0099**			
	(0.0772)**	**(0.0798)**			
Fraction Friends HH inc >80k	**0.0681**	**-0.0278**			
	(0.0549)	**(0.0533)**			
Fraction Friends with Job	**0.3476**	**0.0632**			
	(0.0569)**	**(0.0554)**			
SSI parental income			**-0.0061**		
			(0.0069)		
SSI race				**-0.0099**	**-0.0177**
				(0.0128)	**(0.0178)**
Female		-0.0584	-0.0584	-0.0584	0.0018
		(0.0172)**	(0.0172)**	(0.0172)**	(0.0664)
Hispanic		-0.0026	0.0047	-0.0039	
		(0.0269)	(0.0272)	(0.0272)	
Asian		-0.0577	-0.0586	-0.0632	
		(0.0436)	(0.0436)	(0.0440)	
Black		0.0509	0.0619	0.0581	
		(0.0592)	(0.0596)	(0.0587)	
Other Race		-0.1223	-0.1228	-0.1330	
		(0.1046)	(0.1048)	(0.1049)	
Father College		0.0022	0.0004	0.0010	0.0420
		(0.0246)	(0.0245)	(0.0245)	(0.0749)
Mother College		0.0360	0.0340	0.0347	-0.0019
		(0.0234)	(0.0235)	(0.0234)	(0.0769)
HH income above 80		0.0120	0.0127	0.0109	0.0300
		(0.0160)	(0.0160)	(0.0159)	(0.0633)
Cumulative GPR		0.0784	0.0773	0.0772	0.1246
		(0.0200)**	(0.0198)**	(0.0198)**	(0.0796)
SAT Total		-0.0002	-0.0002	-0.0002	-0.0001
		(0.0001)*	(0.0001)*	(0.0001)*	(0.0002)
Controls for Major	No	Yes	Yes	Yes	Yes
Controls for Cohort and Graduation Date	Yes	Yes	Yes	Yes	Yes
Constant	0.4136	0.5393	0.5781	0.5846	0.2805
	(0.0474)**	(0.1108)**	(0.1016)**	(0.1029)**	(0.4280)
Observations	3303	3303	3303	3303	296 Hispanic Only
R-squared	0.0164	0.2341	0.2339	0.2338	0.4307

Robust standard errors in parentheses
* significant at 5%; ** significant at 1%

Table 15
Network Composition and Anticipated Salary

Dependent Variable: Natural Log of Anticipated Salary

	(1)	(2)	(3)	(4)	(5)
Friends		**0.0007**	**0.0007**	**0.0007**	**0.0004**
		(0.0003)*	**(0.0003)***	**(0.0003)***	**(0.0011)**
Fraction Friends Same Major	**0.0503**	**0.0163**			
	(0.0835)	**(0.0782)**			
Fraction Friends HH inc >80k	**0.0767**	**0.0259**			
	(0.0607)	**(0.0510)**			
Mean Friend Salary	**0.5327**	**0.0654**			
	(0.0798)**	**(0.0779)**			
SSI parental income			**-0.0017**		
			(0.0071)		
SSI race				**0.0106**	**-0.0009**
				(0.0126)	**(0.0175)**
Female		-0.0535	-0.0550	-0.0555	-0.0803
		(0.0157)**	(0.0156)**	(0.0158)**	(0.0632)
Hispanic		0.0294	0.0271	0.0317	0.0000
		(0.0211)	(0.0208)	(0.0215)	(0.0000)
Asian		-0.1457	-0.1381	-0.1320	0.0000
		(0.0984)	(0.0961)	(0.0939)	(0.0000)
Black		0.0514	0.0526	0.0463	0.0000
		(0.0403)	(0.0408)	(0.0393)	(0.0000)
Other Race		-0.0376	-0.0400	-0.0315	0.0000
		(0.0318)	(0.0320)	(0.0332)	(0.0000)
Father College		-0.0175	-0.0177	-0.0168	0.1083
		(0.0216)	(0.0213)	(0.0213)	(0.0616)
Mother College		0.0030	0.0033	0.0044	0.0841
		(0.0224)	(0.0225)	(0.0221)	(0.0777)
HH income above 80		0.0200	0.0231	0.0225	0.1206
		(0.0144)	(0.0142)	(0.0141)	(0.0565)*
Cumulative GPR		0.0653	0.0675	0.0684	-0.0327
		(0.0163)**	(0.0162)**	(0.0162)**	(0.0587)
SAT Total		-0.0001	-0.0001	-0.0001	-0.0008
		(0.0001)*	(0.0001)*	(0.0001)*	(0.0003)**
Controls for Major	No	Yes	Yes	Yes	Yes
Controls for Cohort / Graduation Date	Yes	Yes	Yes	Yes	Yes
Constant	4.9252	9.8400	10.5475	10.5312	11.6370
	(0.8476)**	(0.7899)**	(0.0938)**	(0.0936)**	(0.3263)**
Observations	1333	1333	1349	1349	109
					Hispanic Only
R-squared	0.0562	0.4737	0.4743	0.4745	0.8150

Robust standard errors in parentheses
* significant at 5%; ** significant at 1%

Table A1
Size and Names of Employers

Size of employer-Students Employed	# of Employers	Students Employed
22	1	22
21	1	21
20	1	20
19	1	19
18	1	18
16	2	32
15	2	30
14	3	42
13	3	39
12	5	60
11	3	33
10	4	40
9	2	18
8	4	32
7	4	28
6	14	84
5	9	45
4	30	120
3	55	165
2	121	242
1	878	878
Total	**1,144**	**1,988**

Name	Students Employed
Exxon Mobil	22
Cy Fair ISD	21
Sewell	20
Teach for America	19
Dell	18
Lockheed Martin	16
USAA	16
Mercer	15
Raytheon	15
Accenture	14
Hewlett Packard	14
Mustang Engineering	14

Note: Excludes Military and Texas A&M

Table A2
Descriptive Statisitics
Pairs of Students with Reported Employer

Variable	Mean	Std. Dev.	Min	Max
Same Employer	0.002	0.043	0	1
Difference ln salary *	0.322	0.297	0	4.4
Friends	0.005	0.068	0	1
Friends of Friends	0.083	0.503	0	31
Final GPA diff	0.500	0.368	0	2.2
F04 GPA diff	0.570	0.428	0	4
Same Final college	0.179	0.384	0	1
Same F04 college	0.158	0.364	0	1
Same Final major	0.033	0.178	0	1
Same F04 major	0.031	0.173	0	1
# of Females	1.036	0.706	0	2
# of Blacks	0.027	0.164	0	2
# of Hispanics	0.158	0.381	0	2
# of Asians	0.064	0.250	0	2
# of Whites	1.743	0.473	0	2
# of parental inc>80k	1.197	0.693	0	2
# of father college	1.334	0.666	0	2
# of mother college	1.143	0.700	0	2
SAT Difference	159.1	118.9	0	920
Same High School	0.003	0.056	0	1
Observations		1975078		
* Observations with both Salaries reported		1186570		

Note: All pairs of students in Sample B of Table 2.

Table A3
Facebook Friendship and Same Employer
Probit Model

Dependent Variable: Same Employer				
	(1)	**(2)**	**(3)**	**(4)**
Friends	0.45632	0.39728	0.28832	0.28120
	(0.04476)**	(0.04752)**	(0.04938)**	(0.04944)**
Cohort difference Graduation		-0.00943	-0.00883	-0.00679
		(0.00221)**	(0.00230)**	(0.00297)*
Absolute difference in SAT		-0.00030	-0.00013	-0.00013
		(0.00005)**	(0.00005)**	(0.00005)**
Both Female		0.08140	0.11240	0.12038
		(0.01402)**	(0.01491)**	(0.01498)**
One Female		-0.06568	0.00119	0.00704
		(0.01342)**	(0.01409)	(0.01416)
Same High School		0.20568	0.23400	0.23651
		(0.06674)**	(0.06813)**	(0.06810)**
Final GPA difference			-0.16724	-0.19004
			(0.01631)**	(0.02128)**
Same Final College			0.44828	0.35651
			(0.01241)**	(0.01688)**
Same Final Major			0.40026	0.40875
			(0.01670)**	(0.01824)**
Cohort difference F04				-0.00740
				(0.00805)
F04 GPA difference				0.02719
				(0.01911)
Same F04 College				0.12942
				(0.01710)**
Same F04 Major				-0.02074
				(0.02245)
Controls for Parental Education and Income	No	Yes	Yes	Yes
Controls for Race	No	Yes	Yes	Yes
Controls for Campus Activities	No	No	Yes	Yes
Constant	-2.90971	-2.94832	-3.11659	-3.12581
	(0.00524)**	(0.02580)**	(0.02793)**	(0.02830)**
Observations	1975078	1975078	1975023	1975023

Robust standard errors in parentheses
* significant at 5% level; ** significant at 1% level

Note:
Controls for parental education and income are:
Both Fathers College, One Father College, Both Mothers College, One Mother College, Both HH Income above 80k, One HH income above 80k.
Controls for Race are:
Both Black, Both Hispanic, Both Asian, White-Hispanic, White-Asian, White-Black, Hispanic-Black, Hispanic-Asian, Black-Asian, combinations involving other race.
Controls for Campus Activities are:
Both in Sorority/Fraternity, One in Sorority/Fraternity, Both in Corps of Cadets, One in Corps of Cadets, Both Athlete, One Athlete

Table A4
Facebook Friendship and Same Employer
Employer Adjusted for Size

	Dependent Variable: Same Employer Adjusted for Size			
	(1)	**(2)**	**(3)**	**(4)**
Friends	0.11021	0.10288	0.08513	0.08441
	(0.02863)**	(0.02778)**	(0.02764)**	(0.02762)**
Cohort difference Graduation		-0.00094	-0.00087	-0.00063
		(0.00029)**	(0.00028)**	(0.00036)
Absolute difference in SAT		-0.00003	-0.00001	-0.00001
		(0.00001)**	(0.00001)**	(0.00001)*
Both Female		-0.00015	0.00020	0.00090
		(0.00245)	(0.00247)	(0.00249)
One Female		-0.01431	-0.00850	-0.00801
		(0.00204)**	(0.00203)**	(0.00203)**
Same High School		0.03439	0.03591	0.03603
		(0.02405)	(0.02403)	(0.02402)
Final GPA difference			-0.01154	-0.00933
			(0.00175)**	(0.00229)**
Same Final College			0.03786	0.02821
			(0.00249)**	(0.00362)**
Same Final Major			0.20696	0.20637
			(0.01398)**	(0.01443)**
Cohort difference F04				-0.00082
				(0.00101)
F04 GPA difference				-0.00299
				(0.00207)
Same F04 College				0.01371
				(0.00457)**
Same F04 Major				0.00161
				(0.01064)
Controls for Parental Education and Income	No	Yes	Yes	Yes
Controls for Race	No	Yes	Yes	Yes
Controls for Campus Activities	No	No	Yes	Yes
Constant	0.02759	0.03796	0.02557	0.02541
	(0.00074)**	(0.00374)**	(0.00367)**	(0.00373)**
Observations	1975078	1975078	1975078	1975078
R-squared	0.00005	0.00012	0.00195	0.00197

Robust standard errors in parentheses
* significant at 5% level; ** significant at 1% level

Note:
Controls for parental education and income are:
Both Fathers College, One Father College, Both Mothers College, One Mother College, Both HH Income above 80k, One HH income above 80k.
Controls for Race are:
Both Black, Both Hispanic, Both Asian, White-Hispanic, White-Asian, White-Black, Hispanic-Black, Hispanic-Asian, Black-Asian, combinations involving other race.
Controls for Campus Activities are:
Both in Sorority/Fraternity, One in Sorority/Fraternity, Both in Corps of Cadets, One in Corps of Cadets, Both Athlete, One Athlete

Table A5
Facebook Friendship and Same Employer in Oil/Gas Extraction Industry
Probit Probability Model

Dependent Variable: Same Employer

	(1)	(2)	(3)
Friends	**0.56154**	**0.58178**	**0.51345**
	(0.20875)**	**(0.21752)****	**(0.22173)***
Cohort difference Graduation		-0.02396	-0.02906
		(0.01686)	(0.01935)
Absolute difference in SAT		0.00042	0.00050
		(0.00028)	(0.00028)
Both Female		-0.15688	-0.09585
		(0.09726)	(0.10217)
One Female		-0.14668	-0.12848
		(0.08094)	(0.08254)
Same High School		0.21686	0.26268
		(0.31830)	(0.31421)
Final GPA difference			-0.12173
			(0.18899)
Same Final College			-0.31047
			(0.31745)
Same Final Major			-0.29638
			(0.14178)*
Cohort difference F04			0.04531
			(0.05276)
F04 GPA difference			-0.10118
			(0.14647)
Same F04 College			0.62910
			(0.31864)*
Same F04 Major			0.23895
			(0.14934)
Controls for Parental Education and Income	No	Yes	Yes
Controls for Race	No	Yes	Yes
Controls for Campus Activities	No	No	Yes
Constant	-0.82854	-0.78515	-0.78662
	(0.03362)**	(0.22927)**	(0.24607)**
Observations	1830	1824	1824

Robust standard errors in parentheses
* significant at 5% level; ** significant at 1% level

Note:
Employers are:
Anadarko Petroleum, BP, Chevron, Conoco Phillips, Exxon Mobil, Hess Corp and Shell
Controls for parental education and income are:
Both Fathers College, One Father College, Both Mothers College, One Mother College, Both HH Income above 80k, One HH income above 80k.
Controls for Race are:
Both Black, Both Hispanic, Both Asian, White-Hispanic, White-Asian, White-Black, Hispanic-Black, Hispanic-Asian, Black-Asian, combinations involving other race.
Controls for Campus Activities are:
Both in Sorority/Fraternity, One in Sorority/Fraternity, Both in Corps of Cadets, One in Corps of Cadets, Both Athlete, One Athlete

Table A5
Facebook Friendship and Same Employer
Bivariate Probit

Dependent Variable	Same Employer	Friendship	Same Employer
	Probit	**Bivariate Probit**	
	(1)	**(2)**	**(3)**
Friendship	0.28832		0.41031
	(0.04938)**		(0.21363)
Both Female	0.11240	0.07696	0.11225
	(0.01491)**	(0.01111)**	(0.01491)**
One Female	0.00119	0.01602	0.00119
	(0.01409)	(0.01033)	(0.01409)
Absolute difference in SAT	-0.00013	-0.00040	-0.00013
	(0.00005)**	(0.00003)**	(0.00005)**
Same High School	0.23400	1.85425	0.20229
	(0.06813)**	(0.01909)**	(0.09040)*
Same F04 College		0.07644	
		(0.01519)**	
Same F04 Major		0.20708	
		(0.01825)**	
Cohort difference F04		-0.14619	
		(0.00603)**	
F04 GPA difference		-0.04072	
		(0.01265)**	
Same Final College	0.44828	0.08870	0.44801
	(0.01241)**	(0.01424)**	(0.01242)**
Same Final Major	0.40026	0.19086	0.39931
	(0.01670)**	(0.01785)**	(0.01676)**
Final GPA difference	-0.16724	-0.02211	-0.16711
	(0.01631)**	(0.01465)	(0.01631)**
Cohort difference Graduation	-0.00883	-0.03516	-0.00870
	(0.00230)**	(0.00222)**	(0.00231)**
Controls for Parental Education and Income	Yes	Yes	Yes
Controls for Race	Yes	Yes	Yes
Controls for Campus Activities	Yes	Yes	Yes
Constant	-3.11659	-2.51601	-3.11723
	(0.02793)**	(0.01991)**	(0.02795)**
Observations	1975023	1975078	1975078

Robust standard errors in parentheses
* significant at 5% level; ** significant at 1% level

Note:
Controls for parental education and income are:
Both Fathers College, One Father College, Both Mothers College, One Mother College, Both HH Income above 80k, One HH income above 80k.
Controls for Race are:
Both Black, Both Hispanic, Both Asian, White-Hispanic, White-Asian, White-Black, Hispanic-Black, Hispanic-Asian, Black-Asian, combinations involving other race.
Controls for Campus Activities are:
Both in Sorority/Fraternity, One in Sorority/Fraternity, Both in Corps of Cadets, One in Corps of Cadets, Both Athlete, One Athlete