

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

Adalbert Mayer

Texas A&M University  
[amayer@econmail.tamu.edu](mailto:amayer@econmail.tamu.edu)

November 2009

## *Abstract*

This paper examines the effect of social connections on the initial employment of university graduates. I use a simple search model to illustrate possible effects of social connections on the job-search process, and investigate the resulting empirical predictions. I use a unique dataset that matches post graduation employment data to information on social connections from facebook.com. I find that two facebook friends are four times more likely to work for the same employer after graduation than two random students. This effect is reduced only slightly after accounting for a rich set of control variables. The number of facebook friends is positively associated with the probability a job offer at the time of graduation. I do not find evidence that more diverse or dispersed networks are advantageous in the job search process.

I would like to thank Steven Puller with whom I collected the data used in this paper. I am grateful to Samantha Wilson, Larry Malota, Dustin Moscovitz, and Arnie Vedlitz for their time and assistance in acquiring our data. I received numerous helpful comments from Richard Dunn, Jason Fletcher, Li Gan, Steven Puller, and from participants at the Texas A&M Applied Micro Workshop.

# 1. Introduction

Social connections are viewed as an important factor in the job search process. Employers use referrals to learn about the productivity of workers.<sup>1</sup> Job seekers use family members and friends to obtain information about vacancies.<sup>2</sup> Job search through social networks can theoretically lead to wage differences of equally productive workers,<sup>3</sup> intergenerational persistence in economic outcomes,<sup>4</sup> and differences in labor market outcomes between different ethnic groups.<sup>5</sup> 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.

In this paper, I examine 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 use a simple model to illustrate possible effects of social connections on the job-search process, and investigate the resulting empirical predictions.

My results contribute to the empirical literature on the effects of social interactions on labor market outcomes. The oldest sources of evidence 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.<sup>6</sup> More recent, direct evidence is based on the connection between residential proximity and employment outcomes,<sup>7</sup> and the connection between ethnic background and common employer.<sup>8</sup> My results are most closely

---

<sup>1</sup> Bewley (1999), Montgomery (1991)

<sup>2</sup> Granovetter (1973), Rees (1966), Ioannides and Datcher-Loury (2004), Pellizzari (Forthcoming).

<sup>3</sup> Fontaine (2008), Calvo-Armengol and Zenou (2005), Kugler (2002), Calvo-Armengol and Jackson (2004), Turocy and Mayer (2009), Ioannides and Soetevent (2006)

<sup>4</sup> Calvo-Armengol and Jackson (2009)

<sup>5</sup> Calvo-Armengol and Jackson (2004)

<sup>6</sup> See Granovetter (1973), Rees (1966), Ioannides Datcher Loury (2004), Pellizzari (Forthcoming).

<sup>7</sup> 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.

<sup>8</sup> Dustmann, et al. (2009) show that in Germany members of the same minority group are more likely to work for the same employer.

related to Sacerdote and Marmaros (2002). They report that employment outcomes of randomly assigned dorm-mates at Dartmouth College are correlated.<sup>9</sup>

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. Hence, I observe pre-graduation social connections.

The advantage 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. One drawback of the data is that Facebook friendships are only a proxy for the actual social networks of students. This could lead to attenuation bias and an understatement of the true effects of social connections. At the same time, it is possible that unobserved student characteristics affect both the formation of friendships and students' career choices. This can create a spurious relationship between social connections and employment outcomes. Without a plausible exogenous source of variation to overcome this concern, my approach is to control for observable characteristics to account for factors that drive both friendship formation and career outcomes.

I employ two empirical strategies. First, I construct all possible pairs of students and examine whether socially connected students are more likely to work for the same employer or have similar employment outcomes. Second, I examine the relationship between a student's social network and her employment outcomes.

I find that two facebook friends are four times more likely to work for the same employer after graduation than two random students. This effect is reduced only slightly when controlling for a

---

<sup>9</sup> They also 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.

number of student characteristics, such as major, grades, SAT scores, gender, race and parental background. This strongly suggests that social connections affect the job search process.

At the same time it is known that social networks form along racial and socioeconomic lines.<sup>10</sup> Therefore, it is possible that the effects of social networks on the job search process lead to an association between background characteristics and employment outcomes.<sup>11</sup> However, I am not able to find a connection between common race, parental education or parental income and the probability to work for a common employer.<sup>12</sup> Possibly friendships are formed along racial and socioeconomic lines to some extent but other – potentially random – influences are relatively more important for the formation of relevant social connections.

When I examine the connection between a student’s social network and her 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 the number of facebook friends. Evidence in favor of the first explanation is the lack of a clear association between number of friends and salary. The raw correlation is slightly negative – after adding controls for characteristics and college performance the relationship is positive and significant – but economically small.

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 connection between the clusteredness (a measure of cliquishness) of an individual’s network and either the probability of a job offer or salary.<sup>13</sup> Similarly, I find that the ethnic or economic (based on parental background) diversity of students’ network has no effect on the probability of receiving a job offer or on salary.

---

<sup>10</sup> Mayer and Puller (2008), Sacerdote and Marmaros (2006), and Weinberg (2007)

<sup>11</sup> Calvo-Armengol and Jackson (2004, 2009)

<sup>12</sup> Dustmann et al.(2009) find a positive association for ethnically different groups of immigrants in Germany.

<sup>13</sup> Tassier (2006) uses General Social Survey data and finds evidence supporting Granovetter’s hypothesis.

In section 2, I present a simple job-search model and illustrate how social connections influence the job search process. I derive a list of empirical predictions. Section 3 describes the data. In Section 4, I present the reduced form results. Section 5 concludes.

## 2. Job Search through Social Connections and Empirical Implications

In this section, I present a simple model to illustrate the role of social connections in the job search process. I derive empirically testable predictions of the effects of job search through social connections.

### 2.1 A Model of Job Search

There are  $N$  students, denoted by subscripts  $i$  or  $j$ . I denote student characteristics with  $X_i$ . There are  $K$  firms with potential job openings. Firms are subscripted with the letter  $k$ . Each firm can have multiple vacancies. The probability that student  $i$  receives a job offer from firm  $k$  is given by:

$$m_{ik} = \Phi(\beta_{M0k} + \beta_{MXk} X_i + v_{Mki}).$$

The probability  $m_{ik}$  depends on the likelihood of two events. First, a student is aware of a vacancy and decides to apply for this job. Second, the firm offers the job to the student. The value (either monetary or in utility terms) of a job at firm  $k$  to student  $i$  is given by  $y_{ik}$ :

$$y_{ik} = \beta_{0Yk} + \beta_{XYk} X_i + v_{yki}.$$

I assume that any job offer is preferred to not working at all –  $y_{ik}$  is above the reservation value.<sup>14</sup>

The variable  $E_i = k$  denotes the employer of student  $i$ . Each student receives zero, one, or multiple offers. If she receives no offers she is unemployed. If she receives one offer from firm  $k$  she will accept this offer and work for firm  $k$  and  $E_i = k$ . If she receives more than one offer she will pick the

---

<sup>14</sup> This assumption is not restrictive. Jobs with salaries below the reservation value are equivalent to non-existing offers.

offer with the highest salary. In other words, the value  $y_{ik}$  reflects a ranking of jobs from least to most preferred.

The values of  $m_{ik}$  and  $y_{ik}$  determine the probability that a student finds employment, the probability of working for a certain employer and her expected salary. Results 1 through 5 list some connections between the model parameters and employment outcomes. I use these results to derive predictions of the effects of social connections on the job search process.

**Result 1: The probability that student  $i$  is employed increases in  $m_{ik}$ .**

The probability that student  $i$  is employed is given by:

$$P(\text{employed}) = 1 - \prod_{k=1}^K (1 - m_{ik}).$$

This expression increases in  $m_{ik}$ .

**Result 2: The expected salary of student  $i$  increases weakly in  $m_{ik}$ .**

The salary of  $i$  is given by the maximum  $y_{ik}$  of all offers received by  $i$ . An increase in  $m_{ik}$  leads to a higher expected number of offers, holding all other  $m_{il}$  ( $l \neq k$ ) fixed. More choice cannot lower the highest value but can increase it.

**Result 3: The probability that  $i$  and  $j$  work for the same employer increases in**

$$E(m_{ik}m_{jk}).$$

The probability that students  $i$  and  $j$  work for the same employer is given by:

$$P(E_i = E_j) = \sum_{k=1}^K P(E_i = k)P(E_j = k)$$

$$P(E_i = E_j) = \sum_{k=1}^K m_{ik}m_{jk} (k\_best\_choice\_for\_i)(k\_best\_choice\_for\_j)$$

Both students have to receive an offer from employer  $k$ , and for both students this offer must be their preferred offer. The probability that both students receive an offer from employer  $k$  is given by  $m_{ik}m_{jk}$ . The probability that  $k$  is the preferred offer depends on the ranking of the jobs and on the probability of receiving other offers. The ranking of jobs does not depend on  $m_{ik}$  or  $m_{jk}$ . The probability of other offers does not depend on  $m_{ik}$  or  $m_{jk}$ , but on  $m_{il}$  or  $m_{jl}$ , with  $l \neq k$ .

**Result 4: The expected salary of student  $i$  increases weakly in  $y_{ik}$ .**

The salary of  $i$  is given by the maximum salary of all offers received by  $i$ . An increase in  $y_{ik}$  cannot lower this value but can increase it.

**Result 5: The probability that  $i$  and  $j$  work for the same employer increases in**

$$E(y_{ik}y_{jk}).$$

The probability that students  $i$  and  $j$  work for the same employer is given by:

$$P(E_i = E_j) = \sum_{k=1}^K P(E_i = k) P(E_j = k)$$

$$P(E_i = E_j) = \sum_{k=1}^K m_{ik}m_{jk} (k\_best\_choice\_for\_i)(k\_best\_choice\_for\_j)$$

Both students have to receive an offer from employer  $k$ , and for both students this offer must be their preferred offer. The probability that  $k$  is the preferred offer depends on the ranking of the jobs. The probability that both students rank job  $k$  highly (or both rank  $k$  lowly) increases in  $E(y_{ik}y_{jk})$ . The probability of receiving an offer does not depend on  $y_{ik}$ .

## 2.2 Social connections

Now, I extend the model by introducing social connections. I use the variable  $F_{ij}$  to capture the connection of students  $i$  and  $j$ . It depends on the students' characteristics and a random term,  $e_{ij}$ :

$$F_{ij} = f(X_i, X_j, e_{ij}) .$$

The  $(N-1) \times 1$  vector  $F_i$  contains the social connections of student  $i$ . The  $N \times N$  matrix  $F$  describes the social network of all  $N$  students. Consistent with the data used here I impose two restrictions on  $F$ .

Two students can be either connected  $F_{ij} = 1$  or not connected  $F_{ij} = 0$ ; and social connections are symmetric, i.e.  $F_{ij} = F_{ji}$ . It is possible that students are connected indirectly, through common friends. These friend of friend connections can be captured in a matrix  $N \times N$  matrix  $G = F'F$ .

Social connections can affect job search process in a number of ways. First, information from social connections might be useful in the job *search* process and help to identify job openings.<sup>15</sup> In other words they affect  $m_{ik}$ . Second, social connections may affect the ability to *signal* productivity – employers use referrals to obtain information about potential employees.<sup>16</sup> This the mechanisms may also work through  $m_{ik}$  by increasing the probability of receiving an offer conditional on applying. Signals transmitted through social connections may also affect wage offers. Third social connections may directly lead to *preferences* for a certain employer (e.g. utility is derived from working with friends). This effect operates through  $y_{ik}$ .

I model the effects of social connections by introducing a connection between the error terms of socially connected individuals in the equations that determine  $m_{ik}$  or  $y_{ik}$ . The parameters  $\gamma_M$  and  $\gamma_Y$  capture the strengths of this connection:

$$y_{ik} = \beta_{Y0} + \beta_{Yk} X_i + v_{Yki} + \gamma_{YF} \sum_{j \neq i} F_{ij} v_{Ykj}$$

---

<sup>15</sup> 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), Soetivent and Zenou (2005), Fontaine (2008)

<sup>16</sup> This mechanism is explored by a number of theoretical papers. See Montgomery (1991).

and

$$m_{ik} = \Phi \beta_{M0} + \beta_{Mk} X_i + v_{Mki} + \gamma_{MF} \sum_{j \neq i} F_{ij} v_{Mkj} .$$

This specification is able to generate a number of the predictions about the relationship between social connections and the model parameters  $m_{ik}$  or  $y_{ik}$  . They are listed as results 6 through 11.

First, larger social networks may provide more information and therefore increase the probability of seeing a given opening and receiving a job offer. Such an effect can be generated by the model if the effect of social connections on  $m_{ik}$  or  $y_{ik}$  is positive. Friends provided information but do not hide or steal it. This can be modeled by restricting  $v_{Mki}$  and  $v_{Yki}$  to positive values.

**Result 6: If  $v_{Mki} \geq 0$  more network connections can lead to a higher  $m_{ik}$  .**

$$E(m_{ik}) = E \Phi \beta_{M0} + \beta_{Mk} X_i + v_{Mki} + \gamma_M \sum_{j \neq i} F_{ij} v_{Mkj}$$

If  $v_{Mki} \geq 0$  and  $\gamma_M \geq 0$ ,  $\gamma_M \sum_{j \neq i} F_{ij} v_{Mkj}$  is increasing in  $F_{ij}$  .

**Result 7: If  $v_{Yki} \geq 0$  more network connections can lead to a higher  $y_{ik}$  .**

$$E(y_{ik}) = E \beta_{Y0} + \beta_{Yk} X_i + v_{Yki} + \gamma_Y \sum_{j \neq i} F_{ij} v_{Ykj}$$

If  $v_{Yki} \geq 0$  and  $\gamma_Y \geq 0$ ,  $\gamma_Y \sum_{j \neq i} F_{ij} v_{Ykj}$  is increasing in  $F_{ij}$  .

The network structure can affect how much information is obtained through social connections. Closer knit networks may result in redundant information, while looser wider spread networks provide broader access to information - “the strengths of weak ties”.<sup>17</sup> A measure that

---

<sup>17</sup> Granovetter Mongtomery (1999) Tassier

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 use an example to illustrate the effects of network structure. Students are connected either directly through  $F$  or indirectly through  $G$ . I assume that students are either connected or not, information can be redundant. Hence the connections between students are captured by the

matrix:  $F_{ij}^* = \max\{F_{ij} + G_{ij}, 1\}$ . The probability of receiving a job offer from firm  $k$  is given by:

$$m_{ik} = \Phi \beta_{M0} + v_{Mki} + \gamma_{MF} \sum_{j \neq i} F_{ij}^* v_{Mkj} .$$

Figure 1 displays two network structures. The friendship matrix  $F$ , the friend of friend matrix  $G$  and the connectivity matrix  $F^*$  are displayed as well. It can be seen that in for network  $A$  the friendship matrix and the friend of friend matrix are identical; while they differ for network  $B$ . If information can be redundant network  $B$  leads to the spread of more information, even though the total number of connections is identical. Student 1 has 2 friends in either network. In network  $A$  her friends are friends with each other and the cluster coefficient of student 1 is equal to one. In network  $B$  her friends are not connected and her cluster coefficient is equal to zero. Due to the redundancy of the friend and the friend of friend networks in network  $A$ , student 1 can obtain more information in network  $B$ .

**Result 8: The network structure (cluster coefficient) can affect  $m_{ik}$ .**

See example above.

**Result 9: More dispersed network (strengths of weak ties) can lead to higher  $y_{ik}$ .**

See example above – applied to  $y_{ik}$  instead of  $m_{ik}$ .

Finally, results 10 and 11 show that the models leads to a correlation in the draws of  $m_{ik}$  or  $y_{ik}$  of socially connected students.

**Result 10:** If  $F_{ij} > 0$ ,  $E(m_{ik}m_{jk})$  is increasing in  $\gamma_M$ .

$$\text{After conditioning on X: } E(m_{ik}m_{jk}) = \gamma_M E F_{ij} (v_{Mki}^2 + v_{Mki}^2)$$

**Result 11:** If  $F_{ij} > 0$ ,  $E(y_{ik}y_{jk})$  is increasing in  $\gamma_Y$ .

$$\text{After conditioning on X: } E(y_{ik}y_{jk}) = \gamma_M E F_{ij} (v_{Yki}^2 + v_{Yki}^2) .$$

Many theory papers make the assumption that employed friends pass on information about job openings, while unemployed friends apply themselves and do not pass on information.<sup>18</sup> Moreover, in a network with many unemployed individuals there is more competition for information on vacancies. This means a network with more employed friends or a higher share of employed friends provides more information about job openings (a higher  $m_{ik}$ ). I do not model this relationship but simply state the result and use it to obtain empirical predictions.<sup>19</sup>

**Result 12 (not from model):** Many (a high share of) employed friends increases the probability of employment.

By combining Results 1-5 with Results 6-11 it is possible to obtain empirically testable predictions about the relationship between social connections and employment outcomes. I summarize these predictions in Table 1:

**Prediction 1:** The probability of employment increases in number of network connections.

---

<sup>18</sup> Calvo-Armengol And Jackson, Soetevent and Zenou, Fontaine (2008).

<sup>19</sup> To model this relationship individuals would have to search sequentially. Some individuals search while others already are employed. In the model here all students search simultaneously.

Follows from Results 1 and 6.

**Prediction 2: The probability of employment can depend on the network structure.**

Follows from Results 1 and 8.

**Prediction 3: Expected salary increases in number of network connections.**

Follows from Results 2 and 6 or from 4 and 7.

**Prediction 4: Expected salary depends on network structure.**

Follows from Results 2 and 8 or from 4 and 9.

**Prediction 5: Socially connected students are more likely to work for the same employer.**

Follows from Results 3 and 10 or from 5 and 11.

**Prediction 6: Many (a high share of) employed friends increases the probability of employment.**

From Results 1 and 12.

**Prediction 7: Many (a high share of) employed friends increases the expected salary.**

From Results 2 and 12.

### **2.3 Empirical Specification**

I exploit two kinds of observable relationships to test the predictions listed above. First, I construct all possible pairs of students. I estimate the association between the social proximity and the similarity in employment outcomes of these pairs. Second, I investigate the relationship between characteristics of

an individual's social network and her employment outcomes. My main measure of social connections are facebook friendships. I also consider race and parental income as potential indicators of a student's social environment. My most direct measure of effects on the job search process is the probability that two students share the same employer. Other employment outcomes are expected salary and employment status (either still searching or with a job offer) at the time graduation.

Table 1 displays the regressions I use to test the empirical predictions. Table 1a) lists the regressions where a pair of students is the unit of observation. In regressions 1 through 6, I investigate whether pairs that are socially connected are more likely to work for the same employer (Prediction 5). In regressions 6 and 7 my dependent variable are differences in employment status or expected salary. Table 1b) displays individual level regressions. Regressions 8 through 10 use employment status (either still searching or with job offer) as the dependent variable. Regressions 11 through 13 use log-salary as the dependent variable.

## **2.4 Endogeneity Concerns**

The literature on the formation of social connections emphasizes the importance of homophily (love of the same). Students are more likely to form social connections with those who share similar characteristics. It is possible that students with certain similar characteristics are more or less likely to receive an offer with a certain employer and these same common characteristics make it more likely to be socially connected (Result 10). Similar story can be told for result 11.

The relationships captured in predictions 1 through 5 could also be generated by student characteristics that affect both the formation of social connections and the job search process. It is possible that a characteristic X (energy, likability) is positively correlated with the number of friendships a person forms. At the same time this characteristic may be correlated with the ability to search for job openings. Hence it is possible that a high value of X results in high values of  $m_{ik}$  and leads to a large social network at the same time. This could generate a spurious relationship between

the network size and  $m_{ik}$  (Result 6). A similar story can be told about the relationship between an unobserved characteristic, network size and  $y_{ik}$  (Result 7). It is also possible that unobserved characteristics are related to network structure (clusteredness) and to  $m_{ik}$  and  $y_{ik}$  (Results 8 and 9).

### 3. Data

I link 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 enrollment in sororities / fraternities or residence in a dormitory. 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 to provide information 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 the 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 2005, Facebook.com was essentially an 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, political orientation, music tastes, hobbies 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. These friends are likely to include not only close friends but also the “weak ties” that Granovetter (1973) describes as being important for information transmission. Facebook friendships tend to be not formed online but are a way to communicate. The initial interaction between facebook friends is usually face to face.<sup>20</sup>

Table 2 describes the raw data from these sources. Panel a) displays information for 32570 undergraduates who were enrolled in the fall of 2004. For some students not all the information is available. 19701 of these students in my sample answered the career center survey at graduation. The summary statistics for this sample are displayed in Panel c). 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 my survey sample were using facebook.com in the spring of 2005 – displayed in Panels b) and d).<sup>21</sup> The characteristics of the students on facebook are similar to the overall student body. However, facebook is more popular among, females and the younger cohorts.

---

<sup>20</sup> 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.

<sup>21</sup> I dropped students with missing observations.

Some students are signed up on facebook but do not actively use it. The social connections of these students won't be reflected in their facebook friendships. Therefore, I drop all students who have less 5 facebook friends. The summary statistics of the resulting sample are displayed in Table 3. The characteristics of these students are very similar to those displayed in Panel d) of Table 2. The students have on average 27 facebook friends among the students in the sample. 23% report to plan to go to graduate school and 57% have a job or a job over at the time of graduation. 1356 of the students report a salary.

## **4. Results**

In this section, I explore the predictions obtained in section 2 and summarized in Table 1. First, I look at pairs of students and the most direct measure of an effect of social connections – the probability of working for a common employer. Once I have established that facebook friendships can pick up effects of social interactions in the labor market, I investigate the relationship between employment outcomes and the makeup of an individual's facebook network.

### **4.1. Pair Regressions - Probability of same employer**

I examine the association between social connections and the probability of working for the same employer. I limit my sample to students who report an employer in the survey by the A&M career center. I exclude all students that enlist in the military; I also exclude students who report to work for Texas A&M or an associated organization. This leaves me with a sample of 1988 students – the characteristics of this sample are displayed in Table 4.<sup>22</sup> I construct all possible combinations of two students and obtain almost two millions pairs of students. The characteristics of these pairs are displayed in Table 5. Only .2% of all student pairs work for the same employer. About .5% of all

---

<sup>22</sup> Table A1 displays the size distribution of the employers of the students – and list the biggest employers.

student pairs consist of two facebook friends. Besides facebook friendships, I also consider common race, similar parental background and residence in the same dorm as indicators of social connections.

#### 4.1.1 Facebook Friendship and Common Employer

Panel a) of Table 6 displays the number of student pairs who are facebook friends and /or have the same major. Panel 6 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. Panels 6 c) displays the probability that two students work for the same employer conditional on 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). This is driven in part by the fact that facebook friends are more likely to share the same major – see Panel b). But even after conditioning on common major facebook friends are almost 3 times more likely to work for the same employer.

The probability that a student works for the same company as another A&M graduate depends on the total number of A&M students hired by a company. To account for this mechanical relationship I adjust the probability of working for the same employer for company size.<sup>23</sup> Panel d) displays the relationship between this size adjusted probability and facebook friendship and common major. The results are qualitatively identical and quantitatively similar to those in Panel c).

To further explore if the association between facebook friendship and the probability of sharing a common employer is spurious, I condition on additional characteristics. Table 7 displays the results of regressions of size adjusted probability of same employer on a number of common

---

<sup>23</sup> I calculated 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.

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

characteristics of the pair.<sup>24</sup> Column (1) shows the regression without additional controls – equivalent to the last column of Panel d) in Table 6. In column (2) I add a control for common major. As seen above, common major is clearly associated with the probability of working for the same employer. The effect of facebook friendship drops slightly. In columns (4), (6), (7), and (8) I subsequently add controls for gender, race, difference in SAT scores, parental education, common high school, difference in final GPA, and campus activities (such as sorority or fraternity membership).<sup>25</sup> The coefficient for facebook friendship drops from .11 without any controls to .09 with the full set of controls. It remains both statistically and economically significant.<sup>26</sup> However, it is not possible to rule out that selection based on other – unobserved – characteristics may be responsible for the remaining association between facebook friendship and the probability of common employer.

#### **4.1.2 Race**

Now, I investigate the connection between common race and common employer.<sup>27</sup> Most of the students at Texas A&M are white, the largest minority are Hispanics. Table 8 displays the number of same race pairs for Whites, Hispanics, Blacks and Asians. It also displays the probability that two students of the same race work for the same employer – overall and conditional on same major. It can be seen that pairs of two Asian students are more likely to work for the same employer than pairs consisting of other race combinations. This result is in part driven by the fact that Asian students are more likely to choose similar majors. Furthermore common characteristics of students or a connection between race and firm size may influence an association between common race and common employer.

---

<sup>24</sup> Table A2 displays the results of linear probability regressions of working for the same employer (without size adjustment) on a number of common characteristics of the pair. The results are very similar to those displayed in Table 7. The coefficient for friends drops slightly as controls for major and background are added (from .005 to .004). It remains economically and statistically significant.

<sup>25</sup> Columns (3) (4) and (9) offer comparisons where I exclude common major or facebook friendship.

<sup>26</sup> In Table A3 and A4 I display the same regression for male (female) pairs only. While facebook friendships are significant for both genders the effect seems stronger for pairs of male students.

<sup>27</sup> Calvo-Armengol and Jackson (2004) illustrate how social networks can lead to (or preserve) differences in of labor market outcomes between social groups (e.g. different ethnic groups).

I address these issues in Table 9. It displays the results of a linear probability regression with the size adjusted probability of working for the same employer as the dependent variable. I only include students that are characterized as either White, Hispanic, Asian, or African American. The independent variables are the racial makeup of a pair and controls for pair characteristics. The omitted category is both white.<sup>28</sup> Pairs of two Asian students are more likely to work for the same employer than two white students. Adding controls for common major, gender, performance and background does not reduce the point estimate by much but the effect is no longer significant at the 5% level.

#### **4.1.3 Parental Background**

In Table 10 I display the probability of working for the same employer conditional on the parental background of a pairs of students.<sup>29</sup> Panel a) presents the raw probabilities and Panel b) the employer size adjusted probabilities. On the right consider only pairs in the same major.

In general the differences between pairs of students from different parental backgrounds are minor. The only group that stands out are pairs of students without college educated parents. This is a very small group of students and it is not possible make any statement with some confidence about this group.<sup>30</sup> In regressions not reported here I find no significant relationship between parental income (parental education) and the probability of working for the same employer.

#### **4.1.4 Dorm-mates and Sorority / Fraternity Membership**

Dorm assignment at A&M is not random. Students' preferences are taken into consideration in the assignment process. Nevertheless, the process is partially random and it is likely that living in

---

<sup>28</sup> I also experimented with specifications where I used mix race pairs, or mixed races pairs and pairs of two Whites as the omitted variable. The results are similar.

<sup>29</sup> Calvo-Armengol and Jackson (2009) show that access to information provided by social networks can lead to intergenerational persistence in economic outcomes.

<sup>30</sup> There are only 10 pairs of students without college educated parents who work for the same employer.

the same dorm increases the probability of social interactions.<sup>31</sup> Panels a) and b) in Table 11 show the probability that two students ever live in the same dorm at the same time conditional on major. Panels c) and d) show that students living in the same dorm are more likely to work for the same employer.

Table 12 shows the results of linear probability model where I regress the (size adjusted) probability of working for the same employer on an indicator of ever residing in the same dorm. Without additional controls there is a statistically significant effect – though much smaller than the effect of a facebook friendship. After including controls the point estimate decreases by half and the coefficient is no longer significant.

In Table 13 I examine the effect of being in any sorority / fraternity. I find no evidence that two students who are both in any sorority or fraternity are more likely to work for the same employer than two random students.

#### **4.2 Pair employment / Salary**

Now, I investigate the association between facebook friendship and employment status or salary. Table 14 reveals that probability that both members of a pair of students are employed is higher if the students are facebook friends. This holds true even after controlling for common characteristics.

Next, I look at the 1701 students who answered the salary question in the survey. Table 15 reveals facebook friends have similar wages. The difference between the salaries of two facebook friends is \$1,600 smaller than the difference between the salaries of two random students. After adding various controls this difference drops by almost half.

#### **4.3 Individual Level Results**

Now, I examine the connection between the characteristics of an individual's social network (size and composition) and her employment outcomes (employment and salary).

---

<sup>31</sup> See Sacerdote and Marmaros (2006)

### 4.3.1 Size of Facebook network – proxy for popularity

Table 16 displays the relationship between having secured employment at the time of graduation and the size of a student's facebook network.<sup>32</sup> Students with more facebook friends are more likely to have found a job at the time of graduation (column 1). This does not change after controlling for demographic characteristics, parental background, college major and grades (column 3). This is consistent with the Prediction 1. The relationship is economically meaningful. 10 additional friends are associated with the same increase (two percentage points) in the probability of employment as an increase in the overall GPA of .25. However, it is also possible that the positive association between the size of a student's facebook network and the probability of being employed is driven by unobserved characteristics. The controls included in column 3 help to reduce the resulting bias but it is not possible to rule out a further bias due to additional unobserved factors. Hence the results are also consistent with the interpretation that students who are likable and socialize are more likely to have characteristics that help them to find employment.

Columns (1) and (3) of Table 17 report the equivalent results with log salary as the dependent variable. Without any controls there is no relationship between number of facebook friends and salary – the point estimate is actually negative. After controlling for personal characteristics, grades, and background more facebook friends are associated with a higher salary. Such an association is consistent with Prediction 3. Again an alternative explanation is that characteristics that are associated with a high number of facebook friends also lead to higher wages. The pattern that the association between number of facebook friends and salary is negative without controls, and positive with controls could be explained by the fact that students who are active on facebook tend to choose majors that are rewarded to a lesser extent or that they have lower grades.

Comparing the results of Tables 16 and 17 suggest that facebook friendships are more strongly associated with the ability to find employment than with the salary conditional on having secured employment.

---

<sup>32</sup> I only include students in this regression who do not plan to continue their education in graduate school.

### **4.3.2 Clusteredness / Diversity of the social network**

In Columns (2) and (4) of Table 16, 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 the looser networks are more useful to obtain information about employment opportunities we would expect to see a negative effect of the cluster coefficient. This is not the case and I cannot confirm Prediction 3. Columns (2) and (4) of Table 17 report the equivalent exercise with log salary as the dependent variable. Again I find no association between the clusteredness of the social network and salary. I cannot confirm Prediction 4.

To measure the diversity of an individual's social network I calculate the Social Segregation Index (SSI)<sup>33</sup> of each student's facebook network for race and parental income. I find no association between either SSI measure and employment status or salary.

### **4.3.3 Friend Characteristics**

In column (1) of Table 18 I report the relationship between the probability of being employed at the time of graduation and the number of employed friends on facebook. I find a positive association and the effect is stronger than effect of the number of facebook friends (employed or unemployed) on employment as seen in Table 16. In Column (2) I regress employment status on the fraction of friends who are employed. There is a strong association between the two variables. In column (3) I include controls for the students' academic performance, major, parental background, cohort and graduation date. The coefficient of fraction of friends employed is still positive but smaller and no longer significant at the 5% level. However, it is still meaningful and significant at the 10% level. In columns (4) and (5) I add controls for the characteristics of the friends of a student. The coefficient for the fraction of friends employed does not change much. Overall I find some weak evidence that students with a higher share of employed friend are more likely to be employed (Prediction 6). The

---

<sup>33</sup> See Echinique and Fryer (2007)

initially strong effect is partially explained by student characteristics – in other words students with many employed friends tend to be in certain majors and get good grades. There remains some weak evidence that having a network with many employed friends is associated with a higher probability of finding employment.

## **5. Conclusion**

I provide evidence that social connections influence the process that matches college graduates to employers. One explanation for this data pattern is the presence of search or matching frictions. Students and/or employers use information from social contacts to reduce these frictions. An alternative explanation is that individuals derive utility from working with friends. Both explanations suggest that friendship formation influences labor market outcomes.

It is known that homophily (a preference for friends with similar characteristics) is an important factor in the friendship formation process. This could lead to intergenerational persistence in economic outcomes, and differences in labor market outcomes between different ethnic groups. However, conditional on graduation from Texas A&M, I do not find a relationship between race or parental background and the probability of working for the same employer. While friendships are formed along racial and socioeconomic lines other – potentially random – influences are relatively more important for the formation of relevant social connections.

Future research might reveal how social connections affect the search process. We still do not know to what extent the social connections are used to overcome search frictions and whether other mechanisms of information transmission are good substitutes.

## References

- Arrow Kenneth J. and Ron Borzekowski (2004) "Limited Network Connections and the Distribution of Wages" *FEDS Working Paper No. 2004-41*
- Bayer Topa Ross (2008) "Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes" *Journal of Political Economy*
- Bewley Truman (1999) "Why Wages Don't Fall during a Recession" Harvard University Press
- Calvo-Armengol, Antoni (2004), "Job Contact Networks," *Journal of Economic Theory*, 115, 1, 191-206.
- Calvo-Armengol, Antoni, Jackson, Matthew O., 2004. The effects of social networks on employment and inequality. *American Economic Review* 94 (3) (June).
- Calvo-Armengol, Antoni, Matthew O. Jackson, 2009. "Like Father, Like Son: Network Externalities, Parent–Child Correlation in Behavior, and Social Mobility", *American Economic Journal: Microeconomics* Vol. 1, No. 1, 124-150, 2009
- Calvo-Armengol Antoni and Yves Zenou (2005) "Job matching, social network and word-of-mouth communication" *Journal of Urban Economics*, 57, 500-522
- Dustmann, Gitz, and Schoenberg (2009) "Job Search Networks and Ethnic Segregation in the Workplace" mimeo, University College London
- Echenique, Federico and Roland Fryer, 2007. "A measure of segregation based on social interactions" *Quarterly Journal of Economics*. 122 (2) (May).
- Fontaine Francois (2008) "Why are similar workers paid differently?" *Journal of Economic Dynamics and Control* Volume 32, Issue 12, December 2008, Pages 3960-3977
- Granovetter, Mark S., 1973. The Strength of Weak Ties. *American Journal of Sociology* 78 (6).

Granovetter, M. 1983. The strength of weak ties: A network theory revisited. *Sociological Theory* 1:201–33.

Granovetter, M. 1995. *Getting a job: A study of contacts and careers*. 2nd edition. Cambridge, MA: Harvard University Press.

Hellerstein, McInerney, and Neumark (2009) “Neighbors and Co-Workers: The Importance of Residential Labor Market Networks” Mimeo

Ioannides, Yannis M. and Linda Datcher Loury, 2004. Job information networks, neighborhood effects and inequality. *Journal of Economic Literature* 42 (4) (December).

Ioannides, Yannis M. and Adriaan R. Soetevent (2006) “Wages and Employment in a Random Social Network with Arbitrary Degree Distribution” *American Economic Review*, 96, 2

Jackson, Matthew O. (2006) “The Economics of Social Networks” *Advances in Economics and Econometrics, Theory and Applications: Ninth World Congress of the Econometric Society*, Chapter 1, Volume 1, edited by Richard Blundell, Whitney Newey, and Torsten Persson, Cambridge University Press.

Kugler Adriana (2002) “Employee referrals and efficiency wages” *Labour Economics* Vol. 10, Issue 5, October 2003, Pages 531-556 2002

Laschever Ron (2008) *The Doughboys Network: Social Interactions and the Employment of World War I Veterans*. Mimeo

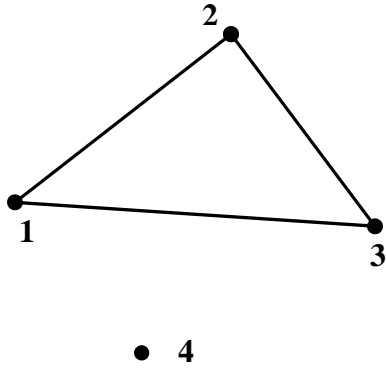
Manski (1993) "Identification and endogenous social effects: the reflection problem," *Review of Economic Studies*, 60 (3), 531–542 (July).

Mayer Adalbert and Puller Steven L., (2008) “The old boy (and girl) network: Social network formation on university campuses” *Journal of Public Economics*, 92 329–347

Montgomery, James D., 1991. Social networks and labor-market outcomes: toward an economic analysis. *American Economic Review* 81 (5).

- Montgomery, James D., 1992 “Job Search and Network Composition: Implications of the Strength-Of-Weak-Ties Hypothesis” *American Sociological Review*, Vol. 57, No. 5 (Oct., 1992), pp. 586-596
- Munshi Kaivan (2003) Networks In The Modern Economy: Mexican Migrants In The U. S. Labor Market *The Quarterly Journal of Economics*, May 2003
- Pellizzari Michele (forthcoming) “Do friends and relatives really help in getting a good job?” *The Industrial and Labor Relations Review*
- Sacerdote Bruce (2001) "Peer Effects With Random Assignment: Results for Dartmouth Roommates." *Quarterly Journal of Economics*, Vol. 116.
- Sacerdote Bruce and David Marmaros (2006) “How do Friendships form?” *The Quarterly Journal of Economics*, Vol. 121, 79-119.
- Sacerdote Bruce and David Marmaros (2002) “Peer and social networks in job search” *European Economic Review*, 46, 870 – 879
- Stinebrickner, Todd R. and Ralph Stinebrickner. “What Can Be Learned About Peer Effects Using College Roommates? Evidence from New Survey Data and Students from Disadvantaged Backgrounds”, *Journal of Public Economics*, Vol. 90, 2006.
- Tassier (2006) “Labor Market Implications of Weak Ties” *Southern Economic Journal*
- Topa Giorgio (2001) “Social Interactions, Local Spillovers and Unemployment” *Review of Economic Studies* Vol.68, 261-295
- Turocy Theodore and Adalbert Mayer (2009) “Price and Wages Dispersion due to heterogeneous arrival of trade opportunities” mimeo
- Weinberg B.(2007) “Social Interactions and Endogenous Association.” Mimeo Ohio State University.

**Figure 1**  
Network Structure

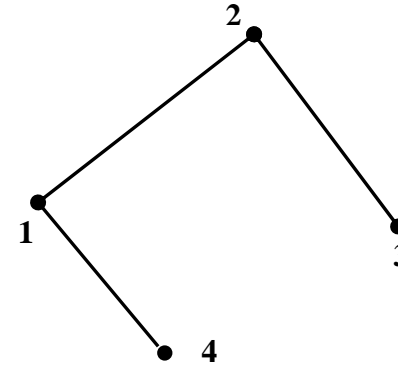


a) Cliquish Network

$$F = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \quad G = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \quad F^* = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$m_{1k} = \Phi(\beta_{M0} + v_{Mk1} + \gamma_{MF}(v_{Mk2} + v_{Mk3}))$$

Cluster coefficient of student  $I$ : 1



b) Open Network

$$F = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix} \quad G = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix} \quad F^* = \begin{pmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{pmatrix}$$

$$m_{1k} = \Phi(\beta_{M0} + v_{Mk1} + \gamma_{MF}(v_{Mk2} + v_{Mk3} + v_{Mk4}))$$

Cluster coefficient of student  $I$ : 0

**Table 1**  
Empirically testable effects of job search with social networks

a) Pair outcomes

#	Prediction	Mechanism	Dependent variable	Independent variable	Table	Result
1	P 5	m,y	Both Same Employer	Both FB Friends	6, 7, A2, A3, A4	Clear association even with controls
2	P 5	m,y	Both Same Employer	Same race	8, 9	No effect after controls
3	P 5	m,y	Both Same Employer	Parental income	10	No significant effect after controls*
4	P 5	m,y	Both Same Employer	Parental Education	10	No effect
5	P 5	m,y	Both Same Employer	Dorm	11,12	No effect after controls
6	P 5	m,y	Both Same Employer	Sorority / Fraternity	13	No effect
7	P 6	m,y	Both employed	Both FB friends	14	Association with controls
8		m,y	Difference Salary	Both FB friends	15	Smaller difference for friends after controls

b) Individual outcomes

#	Prediction	Mechanism	Dependent variable	Independent variable	Table	Result
9	P 1	m	Employment	# friends	16	Small positive association
10	P 2	m	Employment	cluster	16	No association
11	P 6	m	Employment	#/ fraction friends employed	18	Positive effect but not significant after controls
	P 2	m	Employment	SSI		No effect**
12	P 3	m,y	Salary	# friends	17	Very Small positive association after controls. No effect without controls
13	P 4	m,y	Salary	cluster	17	No association
14	P 7	m,y	Salary	#/ fraction friends employed	17	No effect
	P 2	m	Salary	SSI		No effect**

Notes: \* Weak no statistically significant effect for pairs of Asian students  
\*\* Results not reported in this version

**Table 2**  
**Raw data and Sample Selection**

All students enrolled in Fall 04							Students eventually answering the career center survey						
a) All Students				b) Students on Facebook			c) All Students				d) Students on Facebook		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
female	32070	0.50	0.50	8978	0.55	0.50	female	19701	0.52	0.50	5341	0.59	0.49
black	32070	0.02	0.15	8978	0.02	0.14	black	19701	0.02	0.14	5341	0.01	0.12
hispanic	32070	0.10	0.31	8978	0.11	0.31	hispanic	19701	0.09	0.29	5341	0.09	0.29
asian	32070	0.04	0.20	8978	0.04	0.20	asian	19701	0.04	0.19	5341	0.03	0.18
white	32070	0.82	0.38	8978	0.83	0.38	white	19701	0.84	0.37	5341	0.85	0.36
HH_inc_p80k	24623	0.49	0.50	8978	0.56	0.50	HH_inc_p80k	15295	0.51	0.50	5341	0.58	0.49
father_coll	32570	0.87	0.34	11139	0.89	0.31	father_coll	19701	0.88	0.33	5341	0.91	0.28
mother_coll	32570	0.85	0.36	11139	0.88	0.33	mother_coll	19701	0.86	0.35	5341	0.90	0.30
F04Fresh	32070	0.18	0.38	8978	0.24	0.42	F04Fresh	19701	0.09	0.29	5341	0.13	0.34
F04YrSoph	32070	0.21	0.41	8978	0.26	0.44	F04YrSoph	19701	0.21	0.41	5341	0.28	0.45
F04YrJr	32070	0.27	0.44	8978	0.26	0.44	F04YrJr	19701	0.32	0.46	5341	0.33	0.47
F04YrSr	32070	0.34	0.48	8978	0.24	0.43	F04YrSr	19701	0.38	0.49	5341	0.26	0.44
FIGPR_Cum	32070	2.95	0.59	8978	2.97	0.60	FIGPR_Cum	19701	3.08	0.48	5341	3.12	0.47
SAT_total	27924	1150	150	8978	1168	145	SAT_total	17178	1152	148	5341	1170	143
greek	32070	0.13	0.34	8978	0.16	0.37	greek	19701	0.13	0.34	5341	0.17	0.38
corps	32070	0.01	0.12	8978	0.01	0.11	corps	19701	0.01	0.10	5341	0.01	0.10
survey	32570	0.62	0.49	11139	0.67	0.47	survey	19701	1.00	0.00	5341	1.00	0.00
grad_school							grad_school	19701	0.20	0.40	5341	0.23	0.42
Job_salary							Job_salary	6111	45615	13616	2308	45461	12733
got_job							got_job	19701	0.57	0.50	5341	0.57	0.50

**Table 3**  
**Descriptive Statistics**  
**Facebook Sample**

	Mean	Std. Dev.	Min	Max
Female	0.60	0.49	0	1
White	0.86	0.34	0	1
Hispanic	0.09	0.28	0	1
Asian	0.03	0.18	0	1
Black	0.01	0.11	0	1
Father college	0.89	0.32	0	1
Mother college	0.87	0.33	0	1
HH_inc above 80k	0.60	0.49	0	1
SAT_total	1174	141	690	1600
Final GPA	3.14	0.47	1.81	4
Greek	0.19	0.39	0	1
Corps of Cadettes	0.01	0.10	0	1
Grad school	0.23	0.42	0	1
Got job	0.57	0.50	0	1
Job salary*	45718	12484	1250	100000
Friends	26.53	21.38	5	218
Friends of Friends	1126	1197	37	10169
cluster coefficient	0.12	0.08	0	0.47
SSI race	0.85	0.60	0	15.54
SSI parental income	0.62	1.11	0	28.2
Fraction friends female	0.61	0.18	0	1
Fraction friends same race	0.79	0.26	0	1
Fraction friends same major	0.08	0.11	0	1
Fraction friends same high school	0.19	0.18	0	1
Fraction friends hh inc above 80k	0.61	0.15	0	1
Friend mean salary**	45177	6230	9000	77000
Friend mean SAT	1177	57	966	1426.25
Friend mean GPA	3.14	0.16	2.52	3.89

Observations: 4287

Note:

All students with at least 4 facebook friends information on the variables above and information on highschool, dorm, cohort, graduation date, final major and major in fall 04

\* 1356 observations

\*\* 4208 observations

**Table 4**  
**Descriptive Statistics**  
**Students with reported employer names**

	Mean	Std. Dev.	Min	Max
female	0.52	0.50	0	1
black	0.01	0.12	0	1
hisp	0.08	0.27	0	1
asian	0.03	0.18	0	1
white	0.87	0.33	0	1
HH_inc above 80k	0.60	0.49	0	1
SAT_total	1168	140	680	1600
FIGPR_Cum	3.12	0.44	1.809	4
greek	0.18	0.38	0	1
corps	0.01	0.07	0	1
athlete	0.02	0.15	0	1

1988 observations

Note:

All students with information on the variables above and information on highschool, dorm, jobname, cohort, graduation date, major and major in fall 04 and in the last semester recorded

**Table 5**  
**Descriptive Statistics**  
**Pairs of Students with Reported Employer**

Variable	Mean	Min	Max
friends	0.005	0	1
same_job	0.002	0	1
friend_o_f	0.083	0	31
g_both_fem~e	0.268	0	1
g_one_female	0.500	0	1
r_both_white	0.760	0	1
r_both_black	0.0002	0	1
r_both_hisp	0.006	0	1
r_both_asian	0.001	0	1
r_white_bl~k	0.024	0	1
r_white_hisp	0.138	0	1
r_white_as~n	0.056	0	1
r_hisp_black	0.002	0	1
r_hisp_asian	0.005	0	1
r_black_as~n	0.001	0	1
r_other_comb	0.007	0	1
pe_both_coll	0.885	0	1
pe_one_coll	0.112	0	1
pe_both_hinc	0.358	0	1
pe_one_hinc	0.481	0	1
diff_sat	159.1	0	920
same_hs	0.003	0	1
sem_same_d~m	0.018	0	8
same_dorm	0.009	0	1
o_both_greek	0.031	0	1
o_one_greek	0.291	0	1
o_both_crop	0.000	0	1
o_one_crop	0.011	0	1
o_both_ath~e	0.001	0	1
o_one_athl~e	0.044	0	1
cohort_di-04	1.105	0	3
f04_gpa_diff	0.570	0	4
same_f04_c~e	0.158	0	1
same_f04_m~r	0.031	0	1
cohort_dif~d	3.315	0	11
final_gpa_~f	0.500	0	2.191
same_final~e	0.179	0	1
same_final~r	0.033	0	1
Observations	1975078		

**Table 6**  
**Common Employer by Major and Friendship**  
**Pairs of Students**

**a) Frequency**

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

**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	<b>1.0000</b>

**c) Probability of Same Employer**

	Different Major	Same Major	Total
Not friends	0.0014	0.0129	0.0018
Friends	0.0042	0.0326	0.0071
Total	0.0015	0.0132	<b>0.0018</b>

**d) Probability of Same Employer Size Adjusted**

	Different Major	Same Major	Total
Not friends	0.020	0.256	0.028
Friends	0.072	0.728	0.138
Total	0.020	0.263	<b>0.028</b>

---



---

**Table 7**  
**Probability of Common Employer and Facebook Friendship**  
**Adjusted for Employer Size**  
**Linear Probability Estimates**

Dependent Variable: Probability of Same Employer Size Adjusted									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
friends	0.11021 (0.01095)**	0.09384 (0.01094)**	0.10923 (0.01095)**	0.09327 (0.01095)**	0.10400 (0.01110)**	0.08815 (0.01109)**	0.08792 (0.01109)**	0.08832 (0.01112)**	
same_ _major		0.24139 (0.00419)**		0.24010 (0.00419)**		0.23974 (0.00420)**	0.23893 (0.00420)**	0.23887 (0.00420)**	0.23967 (0.00420)**
g_both_female			0.00038 (0.00212)	-0.00119 (0.00211)	-0.00002 (0.00212)	-0.00139 (0.00212)	-0.00135 (0.00212)	-0.00206 (0.00216)	-0.00199 (0.00216)
g_one_female			-0.01414 (0.00187)**	-0.01114 (0.00187)**	-0.01424 (0.00187)**	-0.01117 (0.00187)**	-0.01088 (0.00187)**	-0.01129 (0.00189)**	-0.01130 (0.00189)**
r_black_asian			0.00478 (0.02670)	-0.00209 (0.02668)	0.00705 (0.02672)	-0.00112 (0.02670)	-0.00199 (0.02670)	-0.00077 (0.02671)	-0.00075 (0.02671)
r_both_asian			0.05152 (0.02495)*	0.04149 (0.02493)	0.05224 (0.02496)*	0.04148 (0.02494)	0.04061 (0.02494)	0.04114 (0.02494)	0.04283 (0.02494)
r_both_black			0.01700 (0.05659)	0.01692 (0.05654)	0.01965 (0.05660)	0.01822 (0.05655)	0.01770 (0.05655)	0.01965 (0.05656)	0.02690 (0.05655)
r_both_hisp			0.00147 (0.01298)	-0.00076 (0.01297)	0.00066 (0.01300)	-0.00206 (0.01299)	-0.00268 (0.01299)	-0.00209 (0.01300)	-0.00202 (0.01300)
r_both_white			0.00637 (0.00893)	0.00259 (0.00892)	0.00646 (0.00893)	0.00274 (0.00893)	0.00226 (0.00893)	0.00293 (0.00894)	0.00284 (0.00894)
r_hisp_asian			0.01623 (0.01371)	0.01302 (0.01370)	0.01668 (0.01373)	0.01273 (0.01372)	0.01194 (0.01372)	0.01251 (0.01372)	0.01232 (0.01372)
r_hisp_black			0.00675 (0.01837)	0.00540 (0.01836)	0.00761 (0.01839)	0.00531 (0.01838)	0.00461 (0.01838)	0.00587 (0.01839)	0.00594 (0.01839)
r_white_asian			0.00628 (0.00942)	0.00122 (0.00942)	0.00692 (0.00943)	0.00148 (0.00942)	0.00079 (0.00942)	0.00140 (0.00943)	0.00123 (0.00943)
r_white_black			0.00838 (0.01012)	0.00508 (0.01011)	0.01012 (0.01014)	0.00599 (0.01013)	0.00551 (0.01013)	0.00681 (0.01015)	0.00670 (0.01015)
r_white_hisp			0.00661 (0.00911)	0.00395 (0.00910)	0.00670 (0.00912)	0.00378 (0.00911)	0.00342 (0.00911)	0.00405 (0.00912)	0.00388 (0.00912)
abs diff SAT					-0.00003 (0.00001)**	-0.00002 (0.00001)**	-0.00002 (0.00001)**	-0.00002 (0.00001)**	-0.00002 (0.00001)**
pe_both_coll					-0.02637 (0.01271)*	-0.02721 (0.01270)*	-0.02738 (0.01270)*	-0.02763 (0.01270)*	-0.02761 (0.01270)*
pe_both_hinc					0.00234 (0.00231)	0.00053 (0.00231)	0.00064 (0.00231)	0.00056 (0.00231)	0.00060 (0.00231)
pe_one_coll					-0.02537 (0.01284)*	-0.02566 (0.01283)*	-0.02566 (0.01282)*	-0.02579 (0.01283)*	-0.02587 (0.01283)*
pe_one_hinc					0.00156 (0.00217)	0.00089 (0.00217)	0.00101 (0.00217)	0.00096 (0.00217)	0.00094 (0.00217)
same_hs					0.03433 (0.01353)*	0.03594 (0.01352)**	0.03583 (0.01352)**	0.03568 (0.01352)**	0.05316 (0.01334)**
final_gpa_diff							-0.01185 (0.00204)**	-0.01180 (0.00204)**	-0.01186 (0.00204)**
o_both_athlete								-0.03254 (0.03326)	-0.02762 (0.03326)
o_both_crop								-0.05258 (0.14106)	-0.04326 (0.14106)
o_both_greek								0.00044 (0.00436)	0.00238 (0.00436)
o_one_athlete								-0.00596 (0.00363)	-0.00597 (0.00363)
o_one_crop								-0.00366 (0.00717)	-0.00337 (0.00717)
o_one_greek								0.00243 (0.00168)	0.00237 (0.00168)
Constant	0.02759 (0.00075)**	0.01978 (0.00076)**	0.02808 (0.00896)**	0.02289 (0.00895)*	0.05768 (0.01547)**	0.05263 (0.01546)**	0.05837 (0.01549)**	0.05795 (0.01550)**	0.05839 (0.01550)**
Observations	1975078	1975078	1975078	1975078	1975078	1975078	1975078	1975078	1975078
R-squared	0.00005	0.00173	0.00010	0.00176	0.00012	0.00177	0.00179	0.00179	0.00176

Standard errors in parentheses

\* significant at 5% level; \*\* significant at 1% level

**Table 8**  
**Common Employer by Race**

Composition of Pair	All		Same Major	
	Observations	Share same employer	Observations	Share same employer
Both White	1500778	0.0018	49983	0.0127
Both Hispanic	12246	0.0024	324	0.0185
Both Black	351	0.0028	8	0.1250
Both Asian	2016	0.0040	121	0.0165
One White One Hispanic	272081	0.0021	7685	0.0157
<b>All Pairs</b>	<b>1975078</b>	<b>0.0018</b>	<b>64504</b>	<b>0.0132</b>

**Table 9**  
**Probability of Common Employer Conditional on Race**  
**Adjusted for Employer Size**  
**Linear Probability Estimates**

Dependent Variable: Probability of Same Employer Size Adjusted				
	(1)	(2)	(3)	(4)
r_both_black	0.01943 (0.05582)	0.02084 (0.05581)	0.02222 (0.05581)	0.02286 (0.05583)
r_both_hisp	-0.00484 (0.00949)	-0.00560 (0.00949)	-0.00578 (0.00949)	-0.00628 (0.00953)
r_both_asian	0.04745 (0.02331)*	0.04494 (0.02330)	0.04549 (0.02330)	0.04540 (0.02331)
r_white_black	0.00187 (0.00491)	0.00246 (0.00491)	0.00374 (0.00492)	0.00402 (0.00494)
r_white_hisp	-0.00000 (0.00218)	-0.00022 (0.00218)	-0.00011 (0.00218)	-0.00009 (0.00222)
r_white_asian	-0.00036 (0.00325)	-0.00100 (0.00326)	-0.00050 (0.00326)	-0.00043 (0.00327)
r_hisp_black	0.00047 (0.01608)	0.00070 (0.01608)	0.00155 (0.01608)	0.00156 (0.01611)
r_hisp_asian	0.00965 (0.01047)	0.00819 (0.01047)	0.00897 (0.01047)	0.00867 (0.01050)
r_black_asian	-0.00150 (0.02517)	-0.00198 (0.02517)	-0.00010 (0.02517)	0.00007 (0.02519)
g_both_female		-0.00035 (0.00212)	-0.00078 (0.00212)	-0.00072 (0.00213)
g_one_female		-0.01369 (0.00188)**	-0.01382 (0.00188)**	-0.01378 (0.00188)**
same_f04_major		0.11113 (0.00431)**	0.11065 (0.00431)**	0.11060 (0.00431)**
absolut diff. in SAT			-0.00003 (0.00001)**	-0.00003 (0.00001)**
same_hs			0.05510 (0.01336)**	0.05499 (0.01336)**
pe_both_coll				-0.02530 (0.01280)*
pe_both_hinc				0.00222 (0.00231)
pe_one_coll				-0.02502 (0.01293)
pe_one_hinc				0.00173 (0.00217)
Constant	0.02805 (0.00085)**	0.03160 (0.00163)**	0.03608 (0.00193)**	0.05959 (0.01288)**
Observations	1961190	1961190	1961190	1961190
R-squared	0.00000	0.00039	0.00041	0.00041

Standard errors in parentheses

\* significant at 5% level; \*\* significant at 1% level

**Table 10**  
**Common Employer by Parental background**

**a)**

Composition of Pair	All		Common Major	
	Observations	Share same employer	Observations	Share same employer
Both High Income	707455	0.0020	25847	0.0125
One High Income	949620	0.0018	29670	0.0132
None High Income	318003	0.0017	8987	0.0149
Both College Educated	1747515	0.0018	58207	0.0128
One College Educated	220660	0.0019	6119	0.0165
None College Educated	6903	0.0014	178	0.0112
<b>All Pairs</b>	<b>1975078</b>	<b>0.0018</b>	<b>64504</b>	<b>0.0132</b>

**b)**

Composition of Pair	All		Common Major	
	Observations	Share same employer - Size adjusted	Observations	Share same employer - Size adjusted
Both High Income	707455	0.0288	25847	0.2586
One High Income	949620	0.0279	29670	0.2502
None High Income	318003	0.0270	8987	0.3142
Both College Educated	1747515	0.0280	58207	0.2593
One College Educated	220660	0.0279	6119	0.2676
None College Educated	6903	0.0540	178	1.1236
<b>All Pairs</b>	<b>1975078</b>	<b>0.0281</b>	<b>64504</b>	<b>0.2625</b>

**Table 11**  
**Common Employer by Major and Dorm**

**a) Frequency**

	Different Major	Same Major	Total
Never in Same Dorm	1893429	63,736	1957165
Ever in Same Dorm	17,145	768	17,913
<b>Total</b>	1910574	64,504	<b>1975078</b>

**b) Fraction of pairs**

	Different Major	Same Major	Total
Never in Same Dorm	0.9587	0.0323	0.9909
Ever in Same Dorm	0.0087	0.0004	0.0091
<b>Total</b>	0.9673	0.0327	<b>1.0000</b>

**c) Same Employer**

	Different Major	Same Major	Total
Never in Same Dorm	0.0014	0.0132	0.0018
Ever in Same Dorm	0.0025	0.0117	0.0029
<b>Total</b>	0.0015	0.0132	<b>0.0018</b>

**d) Same Employer Size adjusted**

	Different Major	Same Major	Total
Never in Same Dorm	0.020	0.262	0.028
Ever in Same Dorm	0.034	0.328	0.046
<b>Total</b>	0.020	0.263	<b>0.028</b>

**Table 12**  
**Residing in Same Dorm and the Probability of Common Employer**  
**Linear Probability Estimates**

Dependent Variable: Probability of Same Employer Size Adjusted					
	(1)	(2)	(3)	(4)	(5)
ever in same dorm	0.01844 (0.00786)*	0.01244 (0.00788)	0.01168 (0.00788)	0.01145 (0.00788)	0.00942 (0.00789)
g_both_female		0.00053 (0.00212)	-0.00108 (0.00211)	-0.00129 (0.00212)	0.00108 (0.00212)
g_one_female		-0.01399 (0.00188)**	-0.01098 (0.00187)**	-0.01102 (0.00188)**	-0.00792 (0.00188)**
r_black_asian		0.00464 (0.02671)	-0.00225 (0.02668)	-0.00127 (0.02670)	-0.00265 (0.02670)
r_both_asian		0.05349 (0.02495)*	0.04312 (0.02493)	0.04293 (0.02494)	0.04156 (0.02494)
r_both_black		0.02594 (0.05658)	0.02454 (0.05653)	0.02540 (0.05655)	0.02487 (0.05654)
r_both_hisp		0.00144 (0.01298)	-0.00080 (0.01297)	-0.00209 (0.01299)	-0.00424 (0.01299)
r_both_white		0.00619 (0.00893)	0.00241 (0.00892)	0.00253 (0.00893)	0.00132 (0.00893)
r_hisp_asian		0.01581 (0.01371)	0.01264 (0.01370)	0.01239 (0.01372)	0.01091 (0.01372)
r_hisp_black		0.00667 (0.01837)	0.00532 (0.01836)	0.00527 (0.01838)	0.00395 (0.01838)
r_white_asian		0.00594 (0.00942)	0.00090 (0.00942)	0.00117 (0.00942)	-0.00019 (0.00942)
r_white_black		0.00808 (0.01012)	0.00480 (0.01011)	0.00575 (0.01013)	0.00455 (0.01013)
r_white_hisp		0.00626 (0.00911)	0.00364 (0.00910)	0.00349 (0.00911)	0.00211 (0.00911)
same_final_major			0.24099 (0.00419)**	0.24056 (0.00419)**	0.20762 (0.00456)**
absolut difference SAT				-0.00002 (0.00001)**	-0.00001 (0.00001)*
pe_both_coll				-0.02717 (0.01270)*	-0.02837 (0.01270)*
pe_both_hinc				0.00059 (0.00231)	0.00041 (0.00231)
pe_one_coll				-0.02573 (0.01283)*	-0.02608 (0.01282)*
pe_one_hinc				0.00087 (0.00217)	0.00092 (0.00217)
same_hs				0.05335 (0.01334)**	0.05285 (0.01334)**
cohort_diff_grad					-0.00091 (0.00030)**
final_gpa_diff					-0.01166 (0.00204)**
same_final_college					0.03812 (0.00212)**
Constant	0.02793 (0.00075)**	0.02858 (0.00896)**	0.02328 (0.00895)**	0.05301 (0.01546)**	0.05508 (0.01553)**
Observations	1975078	1975078	1975078	1975078	1975078
R-squared	0.00000	0.00005	0.00172	0.00174	0.00192

Standard errors in parentheses

\* significant at 5% level; \*\* significant at 1% level

**Table 13**  
**Probability of Common Employer**  
**Facebook Friendship and Fraternity / Sorority membership**  
**Adjusted for Employer Size**  
**Linear Probability Estimates**

Dependent Variable: Probability of Same Employer Size Adjusted				
	(1)	(2)	(3)	(4)
friends			0.11021 (0.01095)**	0.08792 (0.01109)**
o_both_greek	0.00721 (0.00429)	0.00163 (0.00432)		
absolut difference in SAT		-0.00002 (0.00001)**		-0.00002 (0.00001)**
final_gpa_diff		-0.01191 (0.00204)**		-0.01185 (0.00204)**
g_both_female		-0.00128 (0.00213)		-0.00135 (0.00212)
g_one_female		-0.01090 (0.00187)**		-0.01088 (0.00187)**
pe_both_coll		-0.02736 (0.01270)*		-0.02738 (0.01270)*
pe_both_hinc		0.00069 (0.00231)		0.00064 (0.00231)
pe_one_coll		-0.02573 (0.01283)*		-0.02566 (0.01282)*
pe_one_hinc		0.00099 (0.00217)		0.00101 (0.00217)
r_black_asian		-0.00195 (0.02670)		-0.00199 (0.02670)
r_both_asian		0.04229 (0.02494)		0.04061 (0.02494)
r_both_black		0.02498 (0.05655)		0.01770 (0.05655)
r_both_hisp		-0.00261 (0.01299)		-0.00268 (0.01299)
r_both_white		0.00217 (0.00893)		0.00226 (0.00893)
r_hisp_asian		0.01175 (0.01372)		0.01194 (0.01372)
r_hisp_black		0.00471 (0.01838)		0.00461 (0.01838)
r_white_asian		0.00063 (0.00943)		0.00079 (0.00942)
r_white_black		0.00541 (0.01013)		0.00551 (0.01013)
r_white_hisp		0.00325 (0.00911)		0.00342 (0.00911)
same_final_major		0.23974 (0.00420)**		0.23893 (0.00420)**
same_hs		0.05324 (0.01334)**		0.03583 (0.01352)**
Constant	0.02788 (0.00076)**	0.05881 (0.01549)**	0.02759 (0.00075)**	0.05837 (0.01549)**
Observations	1975078	1975078	1975078	1975078
R-squared	0.00000	0.00176	0.00005	0.00179

Standard errors in parentheses

\* significant at 5% level; \*\* significant at 1% level

**Table 14**  
**Probability of Both Employed and Facebook Friendship**  
**Linear Probability Estimates**

Dependent Variable: Job Offer at the time of Graduation

	(1)	(2)	(3)	(4)	(5)
friend	0.06633 (0.00267)**	0.07172 (0.00264)**	0.06684 (0.00264)**	0.06587 (0.00264)**	0.06464 (0.00267)**
g_both_female		-0.21077 (0.00049)**	-0.21153 (0.00049)**	-0.21083 (0.00049)**	-0.21035 (0.00049)**
g_one_female		-0.11672 (0.00046)**	-0.11530 (0.00046)**	-0.11422 (0.00046)**	-0.11400 (0.00046)**
r_both_asian		-0.05153 (0.00527)**	-0.05165 (0.00526)**	-0.05191 (0.00526)**	-0.04864 (0.00526)**
r_both_black		0.00269 (0.01115)	0.00262 (0.01114)	0.00347 (0.01114)	0.01363 (0.01113)
r_both_hisp		-0.04292 (0.00182)**	-0.04343 (0.00182)**	-0.04447 (0.00182)**	-0.03723 (0.00182)**
r_both_white		0.04502 (0.00038)**	0.04471 (0.00038)**	0.04418 (0.00038)**	0.03779 (0.00039)**
same_final_college			0.02573 (0.00049)**	0.02547 (0.00049)**	0.02559 (0.00049)**
same_final_major			0.05522 (0.00110)**	0.05278 (0.00110)**	0.05145 (0.00110)**
diff_final_gpa				-0.03566 (0.00044)**	-0.03579 (0.00045)**
diff_sat					0.00000 (0.00000)
pe_both_hinc					0.02975 (0.00038)**
pe_both_lowinc					-0.02857 (0.00046)**
same_high_school					-0.01022 (0.00313)**
Constant	0.45513 (0.00017)**	0.54973 (0.00048)**	0.54378 (0.00049)**	0.56210 (0.00054)**	0.56207 (0.00060)**
Observations	8580153	8580153	8580153	8580153	8580153
R-squared	0.00007	0.02268	0.02365	0.02439	0.02604

Standard errors in parentheses

\* significant at 5% level; \*\* significant at 1% level

**Table 15**  
**Salary Differences**  
**Linear Probability Estimates**

Dependent Variable: Difference in absolute salary					
	(1)	(2)	(3)	(4)	(5)
friend	-1,610.87159 (132.63421)**	-1,511.75130 (132.43430)**	-898.21536 (131.05041)**	-879.65514 (131.01691)**	-908.54559 (132.72789)**
g_both_female		-799.07003 (26.22449)**	-996.71022 (26.00724)**	-1,004.24190 (26.00170)**	-984.74337 (25.99087)**
g_one_female		863.34832 (21.44783)**	541.86086 (21.30688)**	524.20894 (21.31089)**	529.34103 (21.28504)**
r_both_asian		163.20997 (276.49941)	334.62721 (273.49029)	360.48759 (273.41837)	484.61040 (273.01492)
r_both_black		-1,322.94341 (712.66568)	-1,312.74160 (704.90299)	-1,316.30897 (704.71343)	-1,101.56624 (703.70148)
r_both_hisp		32.41423 (113.68822)	-8.06045 (112.45022)	-3.22415 (112.42012)	190.67758 (112.31420)
r_both_white		162.17087 (21.43331)**	180.83119 (21.20043)**	190.45134 (21.19763)**	55.86270 (21.49828)**
same_final_college			-3,412.69692 (24.58200)**	-3,399.08424 (24.58041)**	-3,375.35153 (24.55765)**
same_final_major			-2,386.84371 (52.39156)**	-2,347.65559 (52.39699)**	-2,347.69529 (52.31952)**
diff_final_gpa				686.85002 (25.06549)**	559.74861 (25.14095)**
diff_sat					3.59451 (0.07717)**
pe_both_hinc					618.82721 (20.12819)**
pe_both_lowinc					-637.50154 (26.25536)**
same_high_school					304.38026 (160.69544)
Constant	13,887.16009 (9.20951)**	13,505.90360 (23.04324)**	14,470.29450 (23.52886)**	14,129.48605 (26.60817)**	13,586.07184 (30.68241)**
Observations	1393615	1393615	1393615	1393615	1393615
R-squared	0.00011	0.00387	0.02546	0.02598	0.02905

Standard errors in parentheses

\* significant at 5% level; \*\* significant at 1% level

**Table 16**  
**Probability of Having Employment at the time of Graduation**  
**Linear Probability Estimates**

Dependent Variable: Employment at the Time of Graduation				
	(1)	(2)	(3)	(4)
friends	0.0021 (0.0004)**	0.0020 (0.0014)	0.0015 (0.0004)**	0.0027 (0.0014)*
fr_o_fr		0.0000 (0.0000)		-0.0000 (0.0000)
cluster_coef		0.0010 (0.1278)		-0.0338 (0.1252)
female			-0.0593 (0.0178)**	-0.0586 (0.0179)**
hispanic			0.0008 (0.0281)	-0.0002 (0.0281)
asian			-0.0662 (0.0454)	-0.0679 (0.0455)
black			0.0452 (0.0660)	0.0424 (0.0661)
other_race			-0.1248 (0.1147)	-0.1255 (0.1157)
father_coll			0.0002 (0.0257)	0.0003 (0.0257)
mother_coll			0.0401 (0.0247)	0.0406 (0.0247)
HH income above 80			0.0137 (0.0164)	0.0141 (0.0164)
Cumulative GPR			0.0786 (0.0204)**	0.0796 (0.0205)**
SAT Total			-0.0002 (0.0001)**	-0.0002 (0.0001)**
Controls for Cohort and Graduation Date			Yes	Yes
Controls for Major			Yes	Yes
Observations	3303	3303	3303	3303
R-squared	0.0091	0.0091	0.1824	0.1826

Note:

Students who plan to go to graduate school are excluded.

Robust standard errors in parentheses

Standard errors in parentheses

\* significant at 5%; \*\* significant at 1%

**Table 17**  
**Salary and Network size and Structure**

Dependent Variable: Expected Log Salary at time of graduation						
	(1)	(2)	(3)	(4)	(5)	(6)
friends	-0.0003 (0.0004)	0.0008 (0.0014)	0.0008 (0.0003)*	-0.0004 (0.0009)		
fr_o_fr		-0.0000 (0.0000)		0.0000 (0.0000)		
cluster_coef		0.0230 (0.1324)		0.0468 (0.1053)		
q_fr_female					-0.1323 (0.0468)**	0.0522 (0.0446)
q_fr_sm_race					-0.0283 (0.0334)	-0.0026 (0.0565)
q_fr_hhinc80					0.1453 (0.0592)*	0.0586 (0.0529)
q_fr_sm_major					0.2079 (0.0855)*	0.0105 (0.0752)
q_fr_grad_first					0.1368 (0.0322)**	0.0562 (0.0510)
q_fr_sm_hs					0.0762 (0.0444)	-0.0151 (0.0387)
female			-0.0510 (0.0157)**	-0.0516 (0.0162)**		-0.0530 (0.0164)**
hispanic			0.0307 (0.0202)	0.0316 (0.0204)		0.0307 (0.0447)
asian			-0.1431 (0.0960)	-0.1431 (0.0965)		-0.1411 (0.0814)
black			0.0467 (0.0381)	0.0497 (0.0381)		0.0542 (0.0470)
other_ra			-0.0437 (0.0283)	-0.0440 (0.0269)		-0.0422 (0.0583)
father_coll			-0.0177 (0.0203)	-0.0175 (0.0204)		-0.0154 (0.0204)
mother_coll			-0.0037 (0.0223)	-0.0047 (0.0224)		-0.0030 (0.0222)
HH income above 80			0.0260 (0.0144)	0.0254 (0.0144)		0.0255 (0.0141)
Cumulative GPR			0.0621 (0.0169)**	0.0601 (0.0169)**		0.0619 (0.0172)**
SAT Total			-0.0001 (0.0001)*	-0.0001 (0.0001)*		-0.0001 (0.0001)*
Controls for Cohort and Graduation Date			Yes	Yes		Yes
Controls for Major			Yes	Yes		Yes
Constant	10.6975 (0.0138)**	10.6898 (0.0174)**	9.1492 (1.6870)**	9.0717 (1.6822)**	10.6129 (0.0511)**	9.2452 (1.6990)**
Observations	1372	1372	1372	1372	1372	1372
R-squared	0.0005	0.0011	0.4684	0.4688	0.0265	0.4681

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

**Table 18**  
**Probability of Having Employment at the time of Graduation**  
**Friend Employment and other friend characteristics**  
**Linear Probability Estimates**

Dependent Variable: Employment at the Time of Graduation						
	(1)	(2)	(3)	(4)	(5)	(6)
friends_job	0.0040 (0.0006)**					
q_fr_gotjob		0.3640 (0.0564)**	0.1089 (0.0572)	0.1022 (0.0576)	0.0954 (0.0592)	0.0992 (0.0593)
friend_mean_gpa				-0.0258 (0.0628)	0.0199 (0.0674)	0.0214 (0.0675)
friend_mean_sat				0.0001 (0.0002)	-0.0000 (0.0002)	-0.0000 (0.0002)
friend_coll_par				0.0031 (0.0018)	0.0025 (0.0025)	-0.0043 (0.0069)
friend_hhinc80				-0.0024 (0.0026)	-0.0015 (0.0037)	-0.0017 (0.0037)
friend_same_hs				0.0002 (0.0023)	-0.0001 (0.0023)	-0.0001 (0.0023)
q_fr_female					-0.0824 (0.0505)	-0.0808 (0.0505)
q_fr_sm_race					-0.0550 (0.0649)	-0.0531 (0.0648)
q_fr_hhinc80					-0.0139 (0.0811)	0.0026 (0.0825)
q_fr_sm_major					-0.0175 (0.0830)	-0.0165 (0.0829)
q_fr_grad_first					-0.0879 (0.0511)	-0.0857 (0.0511)
friends						0.0068 (0.0063)
father_coll			0.0042 (0.0258)	-0.0011 (0.0257)	-0.0019 (0.0259)	-0.0008 (0.0259)
mother_coll			0.0449 (0.0247)	0.0399 (0.0246)	0.0394 (0.0247)	0.0400 (0.0247)
HH income above 80			0.0197 (0.0165)	0.0152 (0.0165)	0.0161 (0.0165)	0.0165 (0.0165)
Cumulative GPR				0.0820 (0.0209)**	0.0768 (0.0211)**	0.0774 (0.0211)**
SAT Total			-0.0001 (0.0001)	-0.0002 (0.0001)**	-0.0002 (0.0001)**	-0.0002 (0.0001)**
Controls for Cohort and Graduation Date			Yes	Yes	Yes	Yes
Controls for Major			Yes	Yes	Yes	Yes
Constant	0.6181 (0.0124)**	0.4672 (0.0341)**	-2.2450 (2.1751)	-2.4588 (2.2010)	-3.5301 (2.3467)	-3.5222 (2.3445)
Observations	3303	3303	3303	3303	3303	3303
R-squared	0.0135	0.0125	0.1750	0.1834	0.1851	0.1854

Robust standard errors in parentheses

Standard errors in parentheses

\* significant at 5%; \*\* significant at 1%

**Table A1**  
**Size and Names of Employers**

Size of employer- Students Employed	# of Employers
1	2,817
2	340
3	99
4	42
5	18
6	14
7	11
8	4
9	2
10	2
12	3
<b>Total</b>	<b>3,352</b>

Name	Students Employed
Chevron	12
Cy Fair ISD	12
Sewell	12
Chase	10
L-3 Communications	10
Cargill	9
Shell	9
Brown&Gay Engineering	8
Mercer	8
NASA	8
St Joseph Hospital	8
Bryan ISD	7
Citigroup	7
Countrywide	7
El Paso Corp.	7
GE	7
Hanover Company	7
Hewlett Packard	7
Kimley Horn	7
Neiman Marcus	7
TX DOT	7
Wells Fargo	7

Note: Excludes Military and Texas A&M

**Table A2**  
**Probability of Common Employer and Facebook Friendship**  
**Linear Probability Estimates**

Dependent Variable: Probability of Same Employer									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
friends	0.00527 (0.00045)**	0.00448 (0.00045)**	0.00521 (0.00045)**	0.00444 (0.00045)**	0.00487 (0.00045)**	0.00411 (0.00045)**	0.00409 (0.00045)**	0.00415 (0.00045)**	
same_fnl_majr		0.01167 (0.00017)**		0.01160 (0.00017)**		0.01157 (0.00017)**	0.01151 (0.00017)**	0.01152 (0.00017)**	0.01156 (0.00017)**
g_both_female			0.00058 (0.00009)**	0.00051 (0.00009)**	0.00056 (0.00009)**	0.00049 (0.00009)**	0.00049 (0.00009)**	0.00047 (0.00009)**	0.00047 (0.00009)**
g_one_female			-0.00034 (0.00008)**	-0.00019 (0.00008)**	-0.00035 (0.00008)**	-0.00020 (0.00008)**	-0.00018 (0.00008)**	-0.00019 (0.00008)**	-0.00019 (0.00008)**
r_black_asian			0.00135 (0.00109)	0.00101 (0.00109)	0.00157 (0.00109)	0.00117 (0.00109)	0.00111 (0.00109)	0.00117 (0.00109)	0.00117 (0.00109)
r_both_asian			0.00349 (0.00102)**	0.00301 (0.00102)**	0.00361 (0.00102)**	0.00309 (0.00102)**	0.00303 (0.00102)**	0.00301 (0.00102)**	0.00309 (0.00102)**
r_both_black			0.00202 (0.00231)	0.00202 (0.00231)	0.00228 (0.00231)	0.00221 (0.00231)	0.00217 (0.00231)	0.00230 (0.00231)	0.00264 (0.00231)
r_both_hisp			0.00205 (0.00053)**	0.00194 (0.00053)**	0.00212 (0.00053)**	0.00199 (0.00053)**	0.00194 (0.00053)**	0.00196 (0.00053)**	0.00196 (0.00053)**
r_both_white			0.00136 (0.00036)**	0.00118 (0.00036)**	0.00137 (0.00036)**	0.00119 (0.00036)**	0.00116 (0.00036)**	0.00116 (0.00036)**	0.00116 (0.00036)**
r_hisp_asian			0.00192 (0.00056)**	0.00176 (0.00056)**	0.00204 (0.00056)**	0.00184 (0.00056)**	0.00179 (0.00056)**	0.00179 (0.00056)**	0.00178 (0.00056)**
r_hisp_black			0.00101 (0.00075)	0.00094 (0.00075)	0.00117 (0.00075)	0.00106 (0.00075)	0.00101 (0.00075)	0.00108 (0.00075)	0.00109 (0.00075)
r_white_asian			0.00147 (0.00039)**	0.00123 (0.00038)**	0.00154 (0.00039)**	0.00127 (0.00038)**	0.00122 (0.00038)**	0.00122 (0.00039)**	0.00121 (0.00039)**
r_white_black			0.00112 (0.00041)**	0.00096 (0.00041)**	0.00128 (0.00041)**	0.00108 (0.00041)**	0.00104 (0.00041)**	0.00111 (0.00041)**	0.00111 (0.00041)**
r_white_hisp			0.00170 (0.00037)**	0.00157 (0.00037)**	0.00174 (0.00037)**	0.00160 (0.00037)**	0.00157 (0.00037)**	0.00158 (0.00037)**	0.00158 (0.00037)**
abs. diff SAT					-0.00000 (0.00000)**	-0.00000 (0.00000)**	-0.00000 (0.00000)**	-0.00000 (0.00000)**	-0.00000 (0.00000)**
pe_both_coll					0.00032 (0.00052)	0.00028 (0.00052)	0.00026 (0.00052)	0.00027 (0.00052)	0.00027 (0.00052)
pe_both_hinc					0.00037 (0.00009)**	0.00028 (0.00009)**	0.00029 (0.00009)**	0.00030 (0.00009)**	0.00030 (0.00009)**
pe_one_coll					0.00045 (0.00052)	0.00044 (0.00052)	0.00044 (0.00052)	0.00044 (0.00052)	0.00044 (0.00052)
pe_one_hinc					0.00016 (0.00009)	0.00013 (0.00009)	0.00014 (0.00009)	0.00014 (0.00009)	0.00014 (0.00009)
same_hs					0.00220 (0.00055)**	0.00228 (0.00055)**	0.00227 (0.00055)**	0.00226 (0.00055)**	0.00308 (0.00054)**
final_gpa_diff							-0.00084 (0.00008)**	-0.00084 (0.00008)**	-0.00085 (0.00008)**
o_both_athlete								-0.00120 (0.00136)	-0.00097 (0.00136)
o_both_crop								-0.00279 (0.00576)	-0.00235 (0.00576)
o_both_greek								-0.00026 (0.00018)	-0.00017 (0.00018)
o_one_athlete								-0.00027 (0.00015)	-0.00027 (0.00015)
o_one_crop								-0.00114 (0.00029)**	-0.00113 (0.00029)**
o_one_greek								0.00002 (0.00007)	0.00002 (0.00007)
Constant	0.00181 (0.00003)**	0.00143 (0.00003)**	0.00042 (0.00037)	0.00016 (0.00037)	0.00011 (0.00063)	-0.00013 (0.00063)	0.00028 (0.00063)	0.00031 (0.00063)	0.00033 (0.00063)
Observations	1975078	1975078	1975078	1975078	1975078	1975078	1975078	1975078	1975078
R-squared	0.00007	0.00242	0.00017	0.00249	0.00021	0.00251	0.00256	0.00257	0.00253

Standard errors in parentheses

\* significant at 5% level; \*\* significant at 1% level

**Table A3**  
**Probability of Common Employer and Facebook Friendship**  
**Adjusted for Employer Size**  
**Linear Probability Estimates**  
**Pairs of two male students**

Dependent Variable: Probability of Same Employer Size Adjusted									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
friends	0.10355 (0.02858)**	0.08462 (0.02856)**	0.10257 (0.02859)**	0.08376 (0.02857)**	0.09738 (0.02897)**	0.07905 (0.02894)**	0.07862 (0.02894)**	0.08013 (0.02898)**	
same_fnl_majr		0.29450 (0.00974)**		0.29422 (0.00974)**		0.29384 (0.00975)**	0.29249 (0.00976)**	0.29241 (0.00976)**	0.29296 (0.00975)**
g_one_female			0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
r_black_asian			-0.04261 (0.05696)	-0.05463 (0.05691)	-0.04224 (0.05700)	-0.05603 (0.05695)	-0.05684 (0.05695)	-0.05641 (0.05696)	-0.05585 (0.05696)
r_both_asian			0.13242 (0.05035)**	0.10961 (0.05031)*	0.13261 (0.05037)**	0.10868 (0.05033)*	0.10737 (0.05033)*	0.10737 (0.05033)*	0.10950 (0.05033)*
r_both_black			-0.05067 (0.13191)	-0.04674 (0.13178)	-0.04978 (0.13193)	-0.04822 (0.13180)	-0.04788 (0.13180)	-0.04704 (0.13183)	-0.04051 (0.13181)
r_both_hisp			-0.01779 (0.02776)	-0.02324 (0.02774)	-0.02207 (0.02782)	-0.02807 (0.02779)	-0.02973 (0.02780)	-0.03020 (0.02780)	-0.02999 (0.02780)
r_both_white			-0.00733 (0.01816)	-0.01259 (0.01815)	-0.00682 (0.01819)	-0.01179 (0.01817)	-0.01291 (0.01817)	-0.01228 (0.01818)	-0.01220 (0.01818)
r_hisp_asian			0.02477 (0.02849)	0.01889 (0.02847)	0.02341 (0.02853)	0.01649 (0.02850)	0.01499 (0.02851)	0.01476 (0.02851)	0.01477 (0.02851)
r_hisp_black			-0.04235 (0.04057)	-0.04397 (0.04053)	-0.04444 (0.04062)	-0.04746 (0.04058)	-0.04824 (0.04058)	-0.04786 (0.04061)	-0.04750 (0.04061)
r_white_asian			-0.00228 (0.01937)	-0.00997 (0.01936)	-0.00161 (0.01939)	-0.00975 (0.01937)	-0.01108 (0.01937)	-0.01074 (0.01938)	-0.01068 (0.01938)
r_white_black			-0.00420 (0.02147)	-0.00755 (0.02145)	-0.00293 (0.02150)	-0.00736 (0.02148)	-0.00797 (0.02148)	-0.00717 (0.02153)	-0.00690 (0.02153)
r_white_hisp			-0.01022 (0.01865)	-0.01531 (0.01863)	-0.01072 (0.01866)	-0.01599 (0.01864)	-0.01725 (0.01865)	-0.01721 (0.01865)	-0.01718 (0.01865)
abs diff in SAT					-0.00004 (0.00001)**	-0.00003 (0.00001)	-0.00002 (0.00002)	-0.00002 (0.00002)	-0.00002 (0.00002)
pe_both_coll					-0.06480 (0.02538)*	-0.06630 (0.02535)**	-0.06668 (0.02535)**	-0.06688 (0.02536)**	-0.06677 (0.02536)**
pe_both_hinc					-0.00417 (0.00570)	-0.00668 (0.00570)	-0.00647 (0.00570)	-0.00654 (0.00571)	-0.00652 (0.00571)
pe_one_coll					-0.06482 (0.02563)*	-0.06598 (0.02561)**	-0.06623 (0.02561)**	-0.06632 (0.02561)**	-0.06633 (0.02561)**
pe_one_hinc					-0.00138 (0.00528)	-0.00243 (0.00527)	-0.00232 (0.00527)	-0.00236 (0.00527)	-0.00239 (0.00527)
same_hs					0.03109 (0.03283)	0.03151 (0.03280)	0.03149 (0.03280)	0.03149 (0.03280)	0.04590 (0.03238)
final_gpa_diff							-0.01559 (0.00513)**	-0.01551 (0.00514)**	-0.01558 (0.00514)**
o_both_athlete								-0.03300 (0.06412)	-0.02835 (0.06409)
o_both_crop								-0.05124 (0.16794)	-0.04284 (0.16792)
o_both_greek								-0.01117 (0.01785)	-0.00958 (0.01784)
o_one_athlete								-0.00778 (0.00800)	-0.00774 (0.00800)
o_one_crop								0.00535 (0.01240)	0.00564 (0.01240)
o_one_greek								0.00538 (0.00475)	0.00523 (0.00475)
Constant	0.03460 (0.00184)**	0.02376 (0.00188)**	0.04165 (0.01804)*	0.03615 (0.01802)*	0.11522 (0.03081)**	0.10988 (0.03078)**	0.11803 (0.03090)**	0.11707 (0.03092)**	0.11727 (0.03092)**
Observations	458403	458403	458403	458403	458403	458403	458403	458403	458403
R-squared	0.00003	0.00202	0.00006	0.00205	0.00010	0.00208	0.00210	0.00210	0.00209

Standard errors in parentheses

\* significant at 5% level; \*\* significant at 1% level

**Table A4**  
**Probability of Common Employer and Facebook Friendship**  
**Adjusted for Employer Size**  
**Linear Probability Estimates**  
**Pairs of two female students**

Dependent Variable: Probability of Same Employer Size Adjusted									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
friends	0.07958 (0.02070)**	0.06416 (0.02069)**	0.07980 (0.02070)**	0.06448 (0.02069)**	0.06432 (0.02099)**	0.04913 (0.02098)*	0.04914 (0.02098)*	0.04800 (0.02110)*	
same_fnl_majr		0.22954 (0.00781)**		0.22944 (0.00781)**		0.22935 (0.00781)**	0.22831 (0.00782)**	0.22808 (0.00782)**	0.22848 (0.00782)**
g_one_female			0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
r_black_asian			0.06068 (0.06833)	0.05423 (0.06827)	0.06375 (0.06837)	0.05605 (0.06832)	0.05449 (0.06832)	0.05933 (0.06836)	0.05875 (0.06836)
r_both_asian			-0.00021 (0.06949)	-0.00180 (0.06943)	-0.00022 (0.06952)	-0.00252 (0.06946)	-0.00336 (0.06946)	0.00051 (0.06950)	0.00083 (0.06950)
r_both_black			-0.00156 (0.13429)	-0.00607 (0.13418)	0.00294 (0.13433)	-0.00239 (0.13422)	-0.00386 (0.13422)	0.00190 (0.13424)	0.00324 (0.13424)
r_both_hisp			0.03096 (0.03427)	0.02874 (0.03424)	0.03243 (0.03435)	0.02969 (0.03432)	0.02967 (0.03432)	0.03343 (0.03440)	0.03314 (0.03440)
r_both_white			0.03742 (0.02573)	0.03064 (0.02571)	0.03798 (0.02574)	0.03083 (0.02572)	0.03040 (0.02572)	0.03300 (0.02579)	0.03266 (0.02579)
r_hisp_asian			0.01176 (0.03705)	0.00816 (0.03702)	0.01382 (0.03712)	0.00951 (0.03709)	0.00892 (0.03709)	0.01274 (0.03716)	0.01237 (0.03716)
r_hisp_black			0.09159 (0.04568)*	0.08814 (0.04565)	0.09426 (0.04576)*	0.09003 (0.04572)*	0.08908 (0.04572)	0.09385 (0.04579)*	0.09354 (0.04579)*
r_white_asian			0.02610 (0.02675)	0.02142 (0.02673)	0.02681 (0.02679)	0.02160 (0.02677)	0.02105 (0.02677)	0.02428 (0.02684)	0.02386 (0.02684)
r_white_black			0.03794 (0.02780)	0.03293 (0.02778)	0.03987 (0.02787)	0.03387 (0.02785)	0.03333 (0.02785)	0.03750 (0.02793)	0.03703 (0.02793)
r_white_hisp			0.03645 (0.02606)	0.03231 (0.02604)	0.03736 (0.02610)	0.03270 (0.02608)	0.03275 (0.02608)	0.03592 (0.02617)	0.03555 (0.02617)
absdiff in SAT					-0.00002 (0.00001)	-0.00001 (0.00001)	-0.00000 (0.00001)	-0.00000 (0.00001)	-0.00000 (0.00001)
pe_both_coll					0.01946 (0.03555)	0.01963 (0.03552)	0.01931 (0.03552)	0.01833 (0.03553)	0.01819 (0.03553)
pe_both_hinc					0.00529 (0.00498)	0.00410 (0.00497)	0.00387 (0.00497)	0.00384 (0.00499)	0.00387 (0.00499)
pe_one_coll					0.02126 (0.03586)	0.02153 (0.03583)	0.02156 (0.03583)	0.02105 (0.03584)	0.02088 (0.03584)
pe_one_hinc					0.00720 (0.00473)	0.00687 (0.00472)	0.00692 (0.00472)	0.00690 (0.00473)	0.00689 (0.00473)
same_hs					0.13149 (0.02962)**	0.13236 (0.02960)**	0.13161 (0.02960)**	0.13145 (0.02960)**	0.14246 (0.02920)**
final_gpa_diff							-0.01516 (0.00446)**	-0.01497 (0.00446)**	-0.01496 (0.00446)**
o_both_athlete								-0.04418 (0.09979)	-0.03884 (0.09976)
o_both_crop								0.00000 (0.00000)	0.00000 (0.00000)
o_both_greek								0.00548 (0.00698)	0.00709 (0.00695)
o_one_athlete								-0.02026 (0.00904)*	-0.02036 (0.00904)*
o_one_crop								0.00000 (0.00000)	0.00000 (0.00000)
o_one_greek								0.00367 (0.00340)	0.00361 (0.00340)
Constant	0.03510 (0.00160)**	0.02513 (0.00164)**	-0.00151 (0.02567)	-0.00524 (0.02565)	-0.02450 (0.04393)	-0.02888 (0.04390)	-0.02166 (0.04395)	-0.02445 (0.04402)	-0.02376 (0.04401)
Observations	529935	529935	529935	529935	529935	529935	529935	529935	529935
R-squared	0.00003	0.00166	0.00004	0.00167	0.00009	0.00171	0.00173	0.00175	0.00174

Standard errors in parentheses

\* significant at 5% level; \*\* significant at 1% level