ESSAYS ON THE EFFECTS OF SOCIAL ABILITY ON LABOR MARKET AND RAIDING

By

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DEDICATION

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ABSTRACT

This dissertation consists of three essays in applied microeconomics. The first and third essays are in the area of empirical labor economics while the second essay utilizes laboratory experiments to study labor market issues. The first essay investigates the effects of social ability on the earnings of employees. Using a microeconomic model in a two-firm setting, the effects of social ability on a worker's earnings are calculated and shown to be increasing with higher social ability levels. The results show that the more social workers, when compared to the less social workers, end up working a lower number of hours but at a higher hourly wage rate. Because of these offsetting effects, social ability had no net effect on annual earnings. The second essay of the dissertation addresses the same issue by using experimental methods. In the constructed experimental design, subjects are randomly selected and assigned to one of two groups, where the second group is the "control" group. A significant relationship is found between how much subjects earned and the ratings they get from their group members for the social group. The highest earnings of the social group are significantly higher than the earnings of the control group. When subjects are assumed to behave rationally, those in the group which spends more time together earn significantly more than those in the control group. The third essay of this dissertation analyzes the findings of Lazear about raiding, seniority within a firm, and job search during time not worked. Using the NLSY-79, a raiding dummy is included in the classical wage equation to better understand its effects. Seniority within a firm and search while unemployed are also included in the wage

equation. Earnings of those who are not raided and stay with the same firm are also compared to those who are raided and switch firms. In both cases, statistically significant results are found confirming the theoretical findings of Lazear. Raiding is associated with higher earnings and staying with the same firm does yield lower earnings. Unemployed search is also examined, and the results support Lazear's statement that search while unemployed yields to lower earnings.

CHAPTER 1. DOES SPENDING MORE TIME WITH COLLEAGUES ACTUALLY PAY YOU?

1.1 Introduction

In the 21st century, using time efficiently is one of the most difficult problems for people to solve. Many people have to decide between having a social life and working or studying to be able to earn more. At the same time, noncognitive skills may be as important as analytical abilities and cognitive skills in the labor market. Some studies report that communications skills, motivation, teamwork, and cooperative skills as well as leadership are all more highly valued than academic achievement and grade-point averages (National Association of Colleges and Employers, 2000). Similarly, employers report a growing importance of *soft skills,* especially for those who are seeking less-educated entry-level workers (Moss and Tilly, 2001). The importance of team work and being a team player is also shown by recent studies (Lindbeck and Snower, 2000). The research in this essay shows that cultivating a social life and spending more time with a diverse field of people could yield higher wages. Thus, this research adds to a growing base of studies demonstrating the role of noncognitive skills in wage determination.

While many studies have been done by sociologists concerning the role of social networking, this is a comparatively new but growing area for economists. Economists have investigated many different factors that can affect people's earnings beyond those considered in standard models. Edward Lazear (1986) constructed a raiding model and proved that it can actually increase the expected wage. One would expect that raiding would occur with higher probability if one knows more people. James Montgomery (1991) analyzed data about job-finding methods and constructed a social-network model, and Francis Green (2000) analyzed data to determine the impact of human-resource policies on social skills. Green characterized workers along two dimensions of ability: social ability and technical ability.

Beauty and height have been shown to affect both men's and women's wages (Hamermesh and Biddle, 1994, 1998). Kuhn and Weinberger (2002) showed that men who occupied leadership positions in high school earned more as adults. The social status of people has also been shown to influence their wages (Ball, Eckel, Grossman, and Zame, 2001). Waddell (2004) showed that poor attitude and low self-esteem in high school graduates leads to fewer years of schooling after secondary education, which affected their job characteristics as well as their job activities and earnings. In recent years, these noncognitive skills have become more important to researchers. Why is this? As the job market saturates with people of similar cognitive skills, employers must make hiring decisions on the basis of noncognitive skills. For these reasons, properties like beauty, height, leadership skills, social status, attitude, and social ability become increasingly important.

A person's social ability is his or her ability to socialize in a society—to connect and interact with people. One can consider social ability just like analytical ability; it is partly genetic and partly due to people's choice to invest in the accumulation of social ability. So, if people like meeting with people, then they will choose to do so. They may also engage in social situations if it is in their best interest to do so, or if they wish to accumulate social ability. Even though people make decisions without necessarily considering the benefits, knowing the possible beneficial outcomes may influence decisions to socialize or not. This research and further analysis will increased the understanding in this area.

In this essay, a model is constructed based on Lazear's (1986) raiding model. Social ability is assumed to affect raiding probability; that is, one's probability of obtaining better offers. After this model is introduced, field data are used to empirically test the model. Next, the effects of social ability are established for hourly wages, number of hours worked, earnings, and wage growth. Results and future research are discussed in the summary and conclusions section.

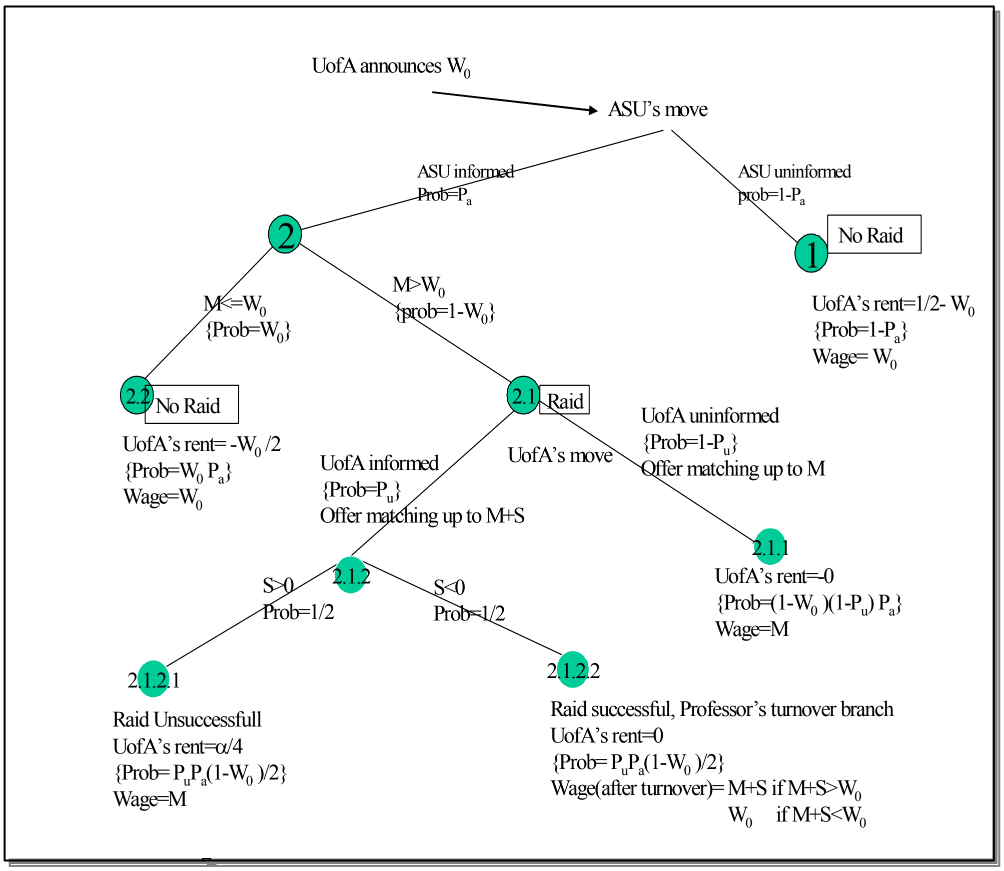
1.2 Theoretical Model

A simple static model is constructed based on Lazear's (1986) raiding model. For simplicity, consider an academic job market with two universities, The University of Arizona (UofA) and Arizona State University (ASU). The UofA has made an offer of wage W_0 to one of its professors for the following year. ASU learns about this offer. The professor's marginal productivity can be learned only by reading his or her CV and academic papers. The professor's marginal productivity is M+S for the UofA and M for ASU. The distributions of the initial wage offer W_0 and the random variable M are uniformly distributed on (0,1). S is uniformly distributed on $[-\alpha/2,\alpha/2]$ where S is a match-specific component and α is bounded on [0,1]. As α increases, the match specific component becomes more important. Thus, α reflects the nature of the job market.

Cashiers at Burger King are less likely to be raided by McDonald's because the job they would be performing does not change much from Burger King to McDonald's or from person to person. So α would be small in this case. However, if one considers managers of two firms, every new match will make a difference even though the basic duties, requirements, and job demands are the same. Likewise, in the academic job market, every new match will be different. In these types of markets, α will be higher. This model is shown in Figure 1.1.

Let P_u represent the probability that UofA is informed about M+S, and let P_a represent the probability that ASU is informed about M. These probabilities will be a function of the professor's social ability. After the UofA announces a wage offer of W_0 that is the optimal offer consistent with zero profit, ASU reacts (as illustrated in Figure 1). ASU is either informed with probability P_a, or uninformed. If it is uninformed, ASU's best strategy is to pass. The UofA can be either informed or uninformed. If the UofA is informed, then the UofA fails to match ASU's offer only when it exceeds M+S. However, it can be easily shown that the expectation of M is always smaller than W_0. If the UofA is uninformed, then the UofA can only base its decision on the fact that ASU has made an offer. If the UofA believes that ASU only raids when it is informed, then it always pays for the UofA to match ASU's offer, in which case ASU's raid cannot succeed. So, this all boils down to the conclusion that ASU's best strategy is to pass when uninformed. (Node 1 in Figure 1) Consequently, no raid will occur at node 1. In this case the expected rent to the UofA will be $1/2 - W_0$, since $E(M+S) = ½$.

Figure 1.1 Raiding Schematic



If ASU is informed about M, there are two possibilities: ASU knows that M > W_0 or knows that M ≤ W_0. When M ≤ W_0, it is clear that it does not pay for ASU to raid. At this node UofA's expected rent,

$$
\begin{aligned}
&= E(M+S \mid M<W_0)-W_0 \\
&= E(M \mid M<W_0)+E(S)-W_0 \\
&= \int_0^{W_0} M.dM \Big/ \int_0^{W_0} dM + 0 - W_0 \\
&= \frac{W_0^{\,2}}{2} \Big/ W_0 \quad - W_0 \\
&= \frac{W_0}{2} - W_0 = -\frac{W_0}{2}
\end{aligned}
\tag{1.1}
$$

When M > W_0, it pays to raid, so ASU will raid and it will be UofA's move. If the UofA is uninformed, it must infer M+S from the fact that ASU raided, so the UofA will match every offer by ASU. But in this case the expected rent will be zero because ASU will stop raiding only when the wage has reached M. If the UofA is informed, the only factor that distinguishes the UofA from ASU at this point is the specific match factor. No one will know the outcome until it has occurred, since the two universities know only their own values. So the expected rent at node 2.1.2.1

$$
\begin{aligned}
&= E(M+S-M \mid M>W_0, S>0) \\
&= E(S \mid M>W_0, S>0) \\
&= \int_0^{\alpha/2} S.dS \Big/ \int_0^{\alpha/2} dS = \frac{\alpha^2}{8} \Big/ \frac{\alpha}{2} = \frac{\alpha}{4}
\end{aligned}
\tag{2.2}
$$

If S < 0, the UofA will lose the bidding war and ASU will get the professor. If W_0 was already sufficiently high, ASU will pay W_0 as a wage. If W_0 was smaller than M+S, then ASU will pay M+S. As can be seen above, the turnover probability will increase as the information probability increases. I will assume $\partial P_i/\partial sa > 0$, where i = a, u and sa is social ability.

$$\begin{aligned}&= 0 = (1-P_a)\left[\frac{1}{2}-W_0\right]+\left(\frac{\alpha}{4}\right)P_uP_a\frac{(1-W_0)}{2}+\left(\frac{-W_0}{2}\right)W_0P_a\\&=\frac{P_aW_0^2}{2}+\left(\frac{\alpha}{8}P_uP_a-P_a+1\right)W_0-\left(\frac{\alpha}{8}P_uP_a-\frac{P_a}{2}+\frac{1}{2}\right)=0\end{aligned} \tag{3.3}$$

Then expected rent will be,

$$W_0=\frac{1}{8P_a}\left\{-\alpha P_aP_u+8P_a-8+/-\sqrt{(\alpha P_aP_u-8P_a+8)^2+16P_a(4-4P_a+\alpha P_aP_u)}\right\} \tag{4.4}$$

From this equation, the roots are,

$$\begin{aligned}W_0&=\frac{1}{8P_a}\left\{-\alpha P_aP_u+8P_a-8+\sqrt{(\alpha P_aP_u+8)^2-64P_a}\right\}\\W_0&=1-\frac{\alpha}{8}P_u-\frac{1}{P_a}+\frac{\sqrt{(\alpha P_aP_u+8)^2-64P_a}}{8P_a}\end{aligned} \tag{5.5}$$

Since we know $W_0 > 0$ and $-\alpha P_aP_u+8P_a-8 < 0$, the result is,

$$W_0=\frac{1}{8P_a}\left\{-\alpha P_aP_u+8P_a-8+/-\sqrt{(\alpha P_aP_u-8P_a+8)^2+16P_a(4-4P_a+\alpha P_aP_u)}\right\} \tag{6.6}$$

This result is positive, because

$$\sqrt{(\alpha P_a P_u - 8P_a + 8)^2 + 16P_a(4 - 4P_a + \alpha P_a P_u)} > \sqrt{(\alpha P_a P_u - 8P_a + 8)^2)} = \alpha P_a P_u - 8P_a + 8 \tag{7.7}$$

When one takes the derivative of W_0 with respect to P_a and social ability, the derivative is negative. The initial wage offer actually decreases if many people know about the individual. This is because the employer takes the greater competition into account when calculating the expected rent. However, the turnover rate will increase, and the expected wage will also increase with an increase in social ability because P_a (the probability of ASU being informed about the professor) increases with social ability. Additionally, from the derivative with respect to P_u (probability of UofA being informed about the professor), an interesting result emerges which is overlooked by Lazear because of his assumption that $P_u = P_a$. If $P_a = 0$, then W_0 will not change when P_u changes. If $P_a > 0$, then W_0 will be increasing in P_u. This makes sense in terms of the theory. If other universities know about an individual, then that individual's wage will increase when he or she is known better by the individual's own university. But if not, the individual's own university would not change their offer even if P_u is changing. So, even if the university knows about the individual with higher probability, it will not change its offer since no other employer is interested or informed of the individual. The probability that $M + S < W_0$ when $S < 0$ is $W_0 + \alpha/2$ and the probability that $M + S > W_0$ when $S < 0$ is $1 - W_0 - \alpha/2$, so the expected wage is calculated as, After rearranging, this equation becomes,

$$
\begin{aligned}
&= (1-P_a)W_0 + P_a(1-W_0)(1-P_u)M + P_uP_a(1-W_0)\frac{W_0+\alpha/2}{2}W_0 + \\
&+ P_uP_a(1-W_0)\frac{1-W_0-\alpha/2}{2}(M+S) + P_uP_a\frac{1-W_0}{2}M + W_0^2P_a
\end{aligned}
\tag{8.8}
$$

After rearranging, this equation becomes,

$$
\begin{aligned}
&= P_aM + \frac{P_uP_aS}{2} - \frac{P_uP_a\alpha(M+S)}{4} \\
&+ W_0\left[1 - P_a - P_aM - \frac{P_aP_u(M+2S)}{2} + \frac{\alpha P_aP_u}{4}(1+M+S)\right] \\
&+ W_0^2\left[\frac{P_aP_u}{2}(1+M+S) + P_a - \frac{\alpha P_aP_u}{4}\right] - W_0^3\frac{P_aP_u}{2}
\end{aligned}
\tag{9.9}
$$

When the derivative is taken with respect to social ability (sa), the first line will be positive because both P_u and P_a are assumed to be dependent on and increasing with respect to social ability. Since all variables are smaller than 1, W_0 is uniformly distributed on (0,1), thus the derivative of the second and the third lines will be smaller, showing that the expected wage is increasing in sa.

1.3 Empirical Model

To examine the impact of social ability on labor market outcomes, I considered its effects on wage rates, hours of work, annual earnings, and wage growth. The variables used in the regression models are defined in Table 1 and discussed in the data section. I also incorporated the measure of having the same employer and the typical measures of education, industry and experience. Therefore the random effects models take the following form:

$$DV_{it} = \alpha_{0it} + \alpha_{1it}\, OUT_{it} + \alpha_{2it}\, X_{it} + r_i + \varepsilon_{it}. \qquad (10.10)$$

I estimate the model for several dependent variables DV_{it} for individual i in year t. They include the log of hourly earnings (LHRATE), the log of annual hours worked (LHOURS), the log of annual earnings (LERNS).

An alternative random effects model used to estimate the effects of social ability on the wage growth (WG) is specified as,

$$\begin{aligned} WG_{it} &= Log\,(Wage_{it}) - Log\,(Wage_{it-1}) \\ WG_{it} &= \gamma_0 + \gamma_1\, OUT_i + \gamma_{2it}\, X_{it} + r_i + \varepsilon_{it} \end{aligned} \qquad (11.11)$$

By performing a 2-stage Heckit calculation, I also hoped to determine whether social ability has any effect on the probability of being unemployed. Including the age and the marital status, the following random effects probit model for the first stage is estimated:

$$Prob(Y_{it}=1) = Prob(\delta_0 + \delta_1\, OUT_i + \delta_2\, AGE_{it} + \delta_3\, MRD_{it} + v_{1it} + \eta_{1i} > 0). \quad (1.12)$$

The second-stage wage-growth equation is then,

$$WG_{it} = \gamma_0 + \gamma_1\, OUT_i + \gamma_{2it}\, X_{it} + \gamma_3\, \lambda_{it} + v_{2it} + \eta_{2i} \qquad (1.13)$$

where λ is the Inverse Mills Ratio.

The following models are also considered:

$$WG_{it} = \gamma_0 + \gamma_1 OUT_i + \gamma_2 SAME_{it} + \gamma_3 EXP_{it} + \gamma_4 EDUC_{it} + \gamma_5 \lambda_{it} + v_{3it} + \eta_{3i} \quad (1.14)$$

$$WG_{it} = \gamma_0 + \gamma_1 OUT_i + \gamma_2 SAME_{it} + \gamma_3 EXP_{it} + \gamma_4 EXPSQ_{it} + \gamma_5 EDUC_{it} + v_{4it} + \eta_{4i} \quad (1.15)$$

1.4 Data

NLSY-79 Cohort Work History Data is used from years 1990, 1992, 1994, 1996, 1998, and 2000. The sample consists of White males. I focus on this group to avoid the confounding effects of children and home duties that often influence the wage and employment decisions of women. There are 1,455 observations for wage rate and hours worked. The same sample is used in both regressions and also in wage growth with a reduced number of observations consisting of 1,214 observations.

In the LHRATE equation, respondents who reported an hourly rate (expressed in terms of cents per hour) less than $1.00 are excluded. The data were collected every year until 1994, and then every two years thereafter. In order to make the analysis consistent, all data were summed to two-year periods. LHRATE is constructed by taking the log of the hourly rate.

For LHOURS, the number of hours worked is reported as weekly data. Respondents reporting negative hours worked were excluded. Then the NLSY created yearly data by totaling the weekly data. Again, the first four years' observations were yearly and the rest were biennial. For consistency, hours worked were summed over two-year periods before the log was taken. LERNS data is created by summing LHOURS and LHRATE because earnings is equal to hourly rate times hours worked.

For social ability, subjects rated themselves as being extremely shy, shy, outgoing, and extremely outgoing on the 1982 survey. This survey will have some bias because subjects rated themselves. Because of insufficient variation in some categories, social ability is categorized into two dummies, OUT and SHY where OUT is equal to 1 for those who report themselves as either outgoing or extremely outgoing and SHY is equal to 1 for those who report themselves as either extremely shy or shy. Since this is a time-invariant variable, the fixed effects model can not be used.[1]

EDUC is the education level of the respondents in years. The SAME variable is a dummy variable created for workers who had the same employer consecutively at the end of each two year period. The respondents were asked if they had the same employer or not. Since, according to the theoretical model, changing jobs can yield a higher wage, it was important to include this variable in my regressions.

IND refers to a vector of dummy industry variables. Respondents were questioned as to the industry of their current or most recent job. Dummies are created according to the NLSY categorization as defined in Table 1.1. In the regressions, PA (public administration) was the excluded industry variable. EXP is normalized experience obtained by dividing total hours worked by 2,000, assuming two 50-week years and 40 hours per week. WG is the growth of total income received from wages. The respondents answered the question about their total income from wages and the data were summed

[1] There was, however, another variable that can be used as a proxy for social ability. The respondents answered the question of how many friends they have among their colleagues. This was also a time-invariant variable. It had less bias, however, because instead of rating themselves, respondents just gave the number of friends they have. This may provide a better estimate of the respondents' social ability. The sample size with this data, however, was very small. Therefore, I focus on the self-reported social ability.

over two-year periods. The sample for this regression is different as mentioned before. Trying to use the same sample might have caused a big reduction in the sample size for both models, so different samples are used. In the 2-stage Heckit model for wage growth, the selection variable, Y, is defined as 0 when wage growth cannot be defined (i.e., when there is not a positive wage for two consecutive observation years. Also when the previous years' total income is 0, wage growth could not be defined. In the probit model, the variable MRD is defined as 1 for when the respondent is married during the observation year.

1.5 Emprical Results

The sample used consists of White males, who have an hourly wage higher than \$1.00 and who positive hours worked as well. The panel data consists of 6 observation years for each person (1990, 1992, 1994, 1996, 1998, 2000) In NLSY, after 1994, data was collected every two years, so to have consistency, data before 1994 are also used only every two years. The social ability variable is time invariant and has two dummies, outgoing and shy. All other variables are time varying. Because the social ability variable was time invariant, a fixed effects model was not used. The BP-LM test rejects OLS in favor of random effects for all three equations. The results are reported in Table 1.2.

In the wage-rate model, the coefficient for OUT is positive and statistically significant in the OLS estimation, and in the random effects estimation. OUT increases hourly rate by 14%. Thus, social ability does appear to affect hourly wages. There are also other interesting trends we can derive from the results in Table 1.2. The coefficient for SAME is positive but not significant. SAME was the dummy variable for having the same employee in consecutive two-year periods. Thus, the effect of not changing one's job on the hourly wages is not significant.

In the LHOURS estimation, the coefficient for OUT is negative, both in OLS and random effects, and it is statistically significant in both models. Thus, those who are social tend to work less. The coefficient for SAME is negative and significant: those employees who keep their jobs work fewer hours than those who are new to the job or the employer. This is also not surprising: in the first year on the job, employees have to prove themselves more. They also need to put in more time to meet the job's learning curve.

Next, the log annual earnings model is estimated. Since OUT has a positive coefficient on the LHRATE model and a negative coefficient on the LHOURS model, these effects offset each other. The results for the coefficient of OUT are positive but statistically insignificant in this model. The coefficient of SAME is negative and statistically significant. Because employees who keep their jobs work less, they earn less as well. One might expect employees who stay with the company to earn more because of wage increases. However, the results suggest the opposite. As shown in the LHRATE model as well, those employees who stayed with the company do not necessarily earn a greater hourly wage as the results for SAME in the LHRATE model are insignificant. The results are reported in Table 1.2.

For the LHRATE, LHOURS, and LERNS models, I suspected that the OUT variable would turn out to be endogenous because the other non-cognitive skills that might affect earnings (beauty, leadership skills, etc.) are all related to social ability and are not controlled for. Consequently, Hausman and Taylor's (1981) estimator is used.

This is an estimator for random effects models to solve the endogeneity problem. I did not have any significant results for the LHRATE and LHOURS models. OUT has a positive coefficient in LERNS model, but it is a weakly significant result. More information about the Hausman and Taylor (1981) estimator and the results is available in an Appendix A.

As expected, in all regressions, the coefficient for EXP is positive and that for EXPSQ is negative. Using the coefficients, we can calculate the year of experience at which the hourly rate peaks: 34 years of experience. Therefore, if somebody enters the labor force at age 18, they will reach their maximum wage rate at age 52. In the first regression for IND, the coefficients for industry variables AGRI, MANUF, TRADE, FINANCE, SERVICE, ENTER, and PROFSERV are all statistically significant and negative. Thus, employees from these industries are getting paid less than those from Public Administration. This wage differential is especially notable for the FINANCE and ENTER variables. In the second regression, the industry variables MANUF, PUBUT, TRADE, FINANCE and SERVICE are all statistically significant and positive, suggesting longer work hours for employees in those industries. EDUC is positive and statistically significant in all three regression models. For IND in the third regression, industry variables CONSTR and PUBUT are the only industry variables with significant and positive coefficients. Therefore, employees from these industries are earning more than those from other fields.

For all wage-growth equations, I looked at the individuals' total income from wages in 1990, 1992, 1994, 1996, 1998, 2000, creating a panel data covering these years.

The data consists of 1,213 observations, 1,100 of which had a job for at least two consecutive periods. The sample is the same sample as the LHRATE model however some individuals lacked either total income from wages or hourly wage data. The results are listed in Table 1.3.

There is a potential issue of selection bias stemming from the fact that for some individuals wage growth cannot be calculated because they lost their jobs. Therefore, I performed a 2-stage Heckit procedure to determine whether social ability has any effect on the probability of being unemployed. Accordingly, Y_i was set to 1 when there is positive wage (total income > 0) for at least two consecutive years and to 0 otherwise. A random-effects probit model was then estimated for the first stage. Finally, the second stage wage growth equation was estimated.

The results are reported in Table 1.3. Random effects could not be estimated in the second stage because the estimated variance of the error for random effects is not positive. In the probit stage, OUT has a negative coefficient and it is statistically significant. Thus, more-social individuals tend to be out of work more often, a highly unexpected result. For the second stage, the Inverse Mills Ratio, λ, is not statistically significant. This means that there is no selection bias. The coefficient for OUT is also statistically insignificant. None of the industry variables have statistically significant effects. [2] For this reason, I removed the IND variables and re-estimated the equation.

[2] I also added age and marital status to the wage growth equation with and without controlling for selection .AGE is statistically significant. However, marital status, Lambda and OUT are not statistically significant. An F-test shows that all of the regressors other than OUT, AGE, EXP and the constant are not jointly statistically significant. Hence, the fundamental conclusions about OUT has not changed.

The results are reported in Table 1.4. Again, the random effects could not be estimated because of an estimated negative error variance. Still, all of the coefficient estimates are statistically insignificant. Then, the same equation is estimated without LAMBDA, because LAMBDA was also insignificant.[3]

Again, the random effects could not be estimated because of a negative estimated variance of random effects. Surprisingly, even though the estimated coefficient for OUT is insignificant, the coefficients for EXP and EXPSQ are significant. The coefficient for EXP is negative: if one has more experience, one's wage growth is smaller. This is understandable: because the wage of an experienced individual is already higher than that of the less-experienced worker, the increase is not as much as that of the less-experienced worker. The coefficient for EXPSQ is positive. The minimum number of years for experience to start increasing wage growth is calculated from these results to be close to 9 years (see Table 1.4)

1.6 Summary and Conclusion

In this essay, by analyzing NLSY 79 Cohort Work History Data, I showed that one's social ability is not statistically significant in determining one's wage rate despite the theory. Using data from 1990–2000 for White males, I created two samples. One of the samples was used in regressions of hourly rate, number of hours, and earnings. Earnings data are created by combining the hourly rate and number of hours. I used

[3] I defined wage growth also on hourly earnings. I found that OUT is not statistically significant in growth of hourly rate and the growth of hours worked.

random effects in all of these regressions because the BP-LM test rejected OLS in favor of random effects. The coefficient of social ability is positive and significant in the hourly rate model and negative and significant in the number of hours worked model in OLS. The random effects results were also statistically significant. Because the respondents rated themselves in the NLSY79 Cohort to create the social ability variable, it may be biased. Additionally, one can suspect social ability of being endogenous, so Hausman and Taylor's (1981) estimator was used in all LERNS, LHOURS and LHRATE models. These results showed that social ability has a positive effect on hourly rate and a negative effect on number of hours worked. Thus these results offset each other and cause insignificant results for the LERNS model.

The same sample was also used to more effectively illustrate the effects of social ability on wage growth. Wage growth was calculated by using the total income from wages in the NLSY79 Cohort. There was a concern about selection, so a 2-stage Heckit procedure was used. In the probit stage, social ability was shown to be negatively effective in keeping a job for at least two consecutive two-year periods. Therefore, those with greater social ability tend to have a higher probability of being out of a job. However, no significant results were found in the second stage. I also tried the wage-growth model without IND variables and with and without EXPSQ. Without EXPSQ, we did not get any significant results, but when we entered EXPSQ, the coefficients for EXP and EXPSQ became significant even though the other variables remained insignificant.

Investing in social ability is becoming a decision as important as investing in cognitive skills given that time is a scarce resource. In the 21st century job market, noncognitive skills are becoming more important, as shown by the literature. Thus, understanding the other determinants of wage will provide a more comprehensive insight for decisions concerning human capital investment. In this study, it is shown that investing more time in improving social ability does have some effect on earnings. There continues to be the need for much additional research in this area. In this essay, I showed the direct effects of White males' social ability on their wage rate and number of hours worked.

There is still much to investigate on the effects of social ability. For example, the effects of social ability need to be studied in more diverse groups than addressed in this initial research. Future studies should focus on women and other ethnic groups. Modeling the accumulation of social ability in time and finding the optimum investment is another important avenue of research in this area. Even research on the effects of social ability in different job markets and in other countries will provide a better understanding of social ability.

In conclusion, this initial study provides an insight into one small segment of the population, and the effects social ability has on their earnings. Further research will broaden the scope of investigation. For this initial study, social skills were shown to have a weak but positive impact on earnings. Laboratory experiments is also used to examine the effects of social ability on earnings in a controlled environment in the following essay.

TABLE 1.1 Variables

LHRATE	Log of hourly rate
LHOURS	Log of number of hours worked over two years.
LERNS	LHOURS + LHRATE, Log of earnings.
OUT	Dummy variable for outgoing and extremely outgoing.
SHY	Dummy variable for shy and extremely shy, left out for regressions.
SAME	Dummy variable for having the same employer the following observation point (two years later)
DIFF	Dummy variable for not having the same employer the following observation point (two years later), left out for regressions.
IND	Industry dummies
AGRI	Agriculture, forestry, and fisheries
MINE	Mining
CONSTR	Construction
MANUF	Manufacturing
PUBUT	Transportation, communications, and public utilities
TRADE	Wholesale and retail trade
FINANCE	Finance, insurance, and real estate
SERVICE	Business, repair, and personal service
ENTER	Entertainment and recreation services
PROFSERV	Professional and related services
PA	Public administration, left out for the regressions.
EXP	Total experience, normalized by dividing total hours worked by 4000, assuming there 50 work weeks per year and 40 hours per week over the 2-year period.

TABLE 1.1-Cont   Variables

EXPSQ	Experience squared
EDUC	Education
Y	Dummy, 1 when wage growth is defined (when there is a wage defined for two consecutive observation points).
AGE	Age at the observation point
MRD	Dummy variable for being married at the observation point
WG	Wage growth over two years (difference of the log wage in two consecutive observation points).

TABLE 1.2 Random Effects Results for OUT Variable

	Hourly Earnings		Log of hours		Log of Annual Earnings	
	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error
Constant	0.7330	0.1420	7.2600	0.1480	7.8800	0.2150
OUT	0.1410	0.0490	-0.0650	0.0390	0.0546	0.0672
(OUT OLS)	(0.0798)	(0.0306)	(-0.0573)	(0.0339)	(0.0224)	(0.0458)
SAME	0.0117	0.0213	-0.1840	0.0303	-0.1406	0.0370
EDUC	0.0794	$0.831\text{x}10^{-2}$	0.0147	$0.72\text{x}10^{-2}$	0.1021	0.0117
AGRI	-0.1877	0.0818	0.054	0.1021	-0.0551	0.1376
MINE	0.0118	0.1606	0.1182	0.1874	0.2322	0.2609
CONSTR	$-0.707\text{x}10^{-2}$	0.0650	0.094	0.0805	0.2097	0.1083
MANUF	-0.155	0.0606	0.185	0.078	0.0941	0.1024
PUBUT	-0.0641	0.0701	0.221	0.0904	0.2062	0.1184
TRADE	-0.1596	0.0593	0.197	0.0762	0.7323	0.1001
FINANCE	-0.1586	0.0813	0.2106	0.0997	0.147	0.1353
SERVICE	-0.1681	0.0619	0.172	0.0801	0.0455	0.1049
ENTER	-0.2460	0.1047	0.178	0.1394	$0.782\text{x}10^{-2}$	0.1781
PROFSERV	-0.2190	0.0625	0.05825	0.08120	-0.08724	0.105
EXP	0.057	$0.837\text{x}10^{-2}$	0.0702	0.0110	0.1258	0.0142
EXPSQ	$-0.663\text{x}10^{-3}$	$0.277\text{x}10^{-3}$	$-0.996\text{x}10^{-3}$	$0.366\text{x}10^{-3}$	$-0.185\text{x}10^{-2}$	$0.471\text{x}10^{-3}$
R^2	0.2557		0.1703		.2835	
NOBS	1414		1446		1405	

TABLE 1.3 Wage Growth in Annual Earnings Model

	WG-OLS		Probit		2-Stage Heckit	
	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error
Constant	-0.0764	0.1915	2.4364	0.6933	-0.0679	0.1950
OUT	-0.0211	0.0537	-0.5451	0.2919	-0.009	0.0740
AGE			0.396×10^{-3}	0.0169		
MRD			0.3644	0.1638		
SAME	0.0160	0.05			0.0170	0.0502
EDUC	0.0156	0.0103			0.0157	0.0103
AGRI	0.0795	0.1611			0.0779	0.1613
MINE	0.0538	0.2781			0.0496	0.2788
CONSTR	0.1148	0.1201			0.1132	0.1204
MANUF	0.1577	0.1177			0.1554	0.1181
PUBUT	0.1979	0.1362			0.1943	0.1371
TRADE	0.0458	0.1150			0.0445	0.1151
FINANCE	0.0435	0.1480			0.0421	0.1482
SERVICE	-0.0626	0.1214			-0.0642	0.1216
ENTER	0.2625	0.2138			0.2630	0.2139
PROFSERV	0.0636	0.1230			0.0613	0.1234
EXP	-0.004	0.005			-0.004	0.005
LAMBDA					-0.3615	1.525
R^2	0.0121				0.0122	
NOBS	1100		1213		1100	

TABLE 1.4 Wage Growth Model Experience Square Comparisons

	WG 2-Stage Heckit without EXPSQ		WG-OLS without EXPSQ		WG-OLS with EXPSQ	
	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error
Constant	0.0371	0.1558	0.0244	0.1530	0.2616	0.2057
OUT	$0.947 \text{x} 10^{-2}$	0.0733	-0.0124	0.0533	-0.0158	0.0533
SAME	0.0203	0.05	0.0150	0.0498	0.0150	0.0498
EDUC	0.0123	$0.931 \text{x} 10^{-2}$	0.0122	$0.930 \text{x} 10^{-2}$	0.0120	$0.929 \text{x} 10^{-2}$
EXP	$-0.723 \text{x} 10^{-2}$	$0.975 \text{x} 10^{-2}$	$-0.644 \text{x} 10^{-2}$	$0.958 \text{x} 10^{-2}$	$-0.718 \text{x} 10^{-2}$	$0.391 \text{x} 10^{-2}$
EXPSQ					$0.412 \text{x} 10^{-2}$	$0.239 \text{x} 10^{-2}$
LAMBDA	-0.6568	1.5098				
R^2	0.0025		0.0024		0.0050	
NOBS	1100		1100		1100	

TABLE 1.5 Hausman and Taylor Estimation Results

	LHRATE		LHOURS		LERNS	
	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error
Constant	0.5407	0.2829	6.983	0.3259	7.464	0.3962
OUT	0.2983	0.3306	0.3626	0.3741	0.7018	0.4556
SAME	0.0151	0.0218	-0.1501	0.3217	-0.1297	0.0380
EDUC	0.0834	$-0.991\text{x}10^{-2}$	0.0126	0.0113	0.0982	0.0138
AGRI	-0.2048	0.0858	0.1074	0.1245	-0.1197	0.1476
MINE	$-0.846\text{x}10^{-2}$	0.1642	0.1755	0.2285	0.2199	0.2724
CONSTR	$-0.514\text{x}10^{-2}$	0.0671	0.1458	0.0960	0.1724	0.1139
MANUF	-0.1600	0.0623	0.2367	0.0900	0.0832	0.1068
PUBUT	-0.0633	0.0720	0.2069	0.1040	0.1694	0.1233
TRADE	-0.1643	0.0606	0.2414	0.0872	0.0739	0.1035
FINANCE	-0.1638	0.0829	0.2699	0.1179	0.1334	0.1402
SERVICE	-0.1719	0.0639	0.1862	0.0917	0.0231	0.1087
ENTER	-0.2530	0.1067	0.2064	0.1550	-0.0279	0.1837
PROFSERV	-0.2088	0.0639	0.1217	0.0922	-0.0761	0.1094
EXP	0.1205	0.0172	0.1356	0.0248	0.2572	0.0295
EXPSQ	$-0.316\text{x}10^{-2}$	$0.114\text{x}10^{-2}$	-0.0046	0.0016	$-0.809\text{x}10^{-2}$	$0.196\text{x}10^{-2}$
NOBS	1405		1405		1405	

CHAPTER 2. SOCIAL ABILITY IN LABOR MARKETS

2.1 Introduction

The word "social" is defined in many different ways. For example, White (1925) defines it as follows:

> With regard to behavior, "social" designates that behavior which is performed by more than one individual, usually a considerable, though indefinite number of individuals. Thus social behavior is behavior that is conditioned by one's fellows. Hence, "social" comes to be equivalent to collective and hence distinguished from individual behavior.

Becker (1967) defines "ability" as the capacity to increase future earnings by current investments in oneself. Hause (1971, 1972) states that such a capacity could be due to a combination of genetic factors, previous investment, experience (including schooling), and other elements that might be difficult to unravel theoretically.

When we combine these two definitions, "social ability" is the ability to be social, and hence develop the capacity to increase earnings by investing in behaving collectively or being in a group setting. Hause's (1972) definition of "ability" perfectly fits with the idea of being "social" as well. Thus, since being social is also part of ability, we can consider ability in two major parts: analytical and social. Therefore, it can be viewed as part of human capital.

Ability is measured using IQ, or related test scores, in many studies (Hause, 1971, 1972; Perl, 1973; Blackburn & Neumark, 1993; Weisbrod & Karpoff, 1968). Bowles, Gintis and Osborne (2001) state this problem of omitting the view of sociological accounts as the non-skill related determinants of earnings under the heading of "socialization for work" (Parsons, 1959; Dreeben, 1967). Bowles, Gintis and Osborne (2001) also construct a model including cognitive skills in the determination of earnings. Other labor market studies (e.g. Green, 2000; Kuhn & Weinberger, 2004; Montgomery, 1991; Waddell, 2006) also show that social skills are becoming as important as analytical ability in the determination of earnings. Since time is a scarce resource, it becomes a choice between investing in social ability or analytical ability. Is it really important to invest in social ability too, or is it just the classical wage determination model that is relevant? This becomes an increasingly important question as the labor market evolves and becomes more competitive.

For years, sociologists looked at the effects of people's behavior on different aspects of life, and earnings is an important factor to consider. The classic wage model should incorporate cognitive skills. For social ability, we can also say it is part of human capital. Especially for jobs that require high skills, social ability is one of the skills that may directly contribute to increase earnings. For other jobs, we can say that social ability affects earnings indirectly, like migration or health.

Economists have investigated many different properties that can affect people's earnings besides the standard human capital model: Hammermesh and Biddle (1994, 1998) show that beauty and height can affect wages; Kuhn and Weinberger (2001) show that men who occupy leadership positions in high school earn more as adults; Ball, Eckel, Grossman and Zame (2001) show that social status affects wages; and Lazear (1986) shows that raiding of employees is an important part of the labor market.

Waddel (2006) shows how poor attitude and self-esteem of high school graduates leads to fewer years of schooling after secondary education and has effects on their job characteristics, on their job activities and earnings. In recent years, these non-cognitive skills have become more important to researchers. Why? Since there are more people in the job market with similar cognitive skills, employers have to make hiring and staffing decisions that also depend on non-cognitive skills. For that reason, individual properties like beauty and height, leadership skills, social status, attitude and social ability become increasingly important in application, and accordingly in research.

Now, the question at hand is: “Are people really better off by having all of their time invested in improving their analytical abilities. Are they really going to earn more by having a higher GPA and not having time for a social life?” This is a question that applies to those who seek to maximize their earnings by maximizing the efficiency of their time. Since time is limited, becoming more social means having less time to study, less time to improve analytical abilities, and less leisure.

Some studies report that communications skills, motivation, teamwork skills and leadership are all now more highly valued than academic achievement (NACE, 2000). Similarly, employers are reporting the growing importance of “soft skills”, especially for those who are seeking less-educated entry-level workers (Moss & Tilly, 2001). This means that investing more time in improving social abilities may be more beneficial than investing more time in improving cognitive skills. More importantly determining the marginal net benefits of each and investing in each until the marginal net benefits are equated. This is a question to address in this essay since there has not been a satisfying answer in the literature. There is the need for much additional research in this area through modeling and finding optimal social ability. For now, these experiments provide some insight into social ability investment.

On the basis of field data, I find little support that social ability affects people's earnings. In this essay, this phenomenon is explored in the laboratory, and such experiments may give a better understanding of how social ability affects one's earnings. In the job market, an individual's relationship with other colleagues or supervisors and what other people are thinking about the individual are as important as the job that the individual performs, particularly so in certain occupations such as lawyers, academicians and doctors. This is well known in the job market where references have so much importance. This research, which incorporates experimental economics, therefore forms part of a growing literature on the role of non-cognitive skills in wage determination.

A person's social ability is, in short, his or her ability to socialize in society, i.e. the ability to connect and interact with people. It is partly genetic, but it is partly people's choices that determine whether they are socially skilled or not. In this respect it is just like an individual's analytical ability: partly genetic, and partly determined by how people chose to spend time to develop these skills. So, if people like meeting with people then they will, thus developing social ability. They will choose to do so if it is perceived to be in their best interest.

Finding suitable field data that measure social ability is difficult, and such a measure is biased since most of the information is gathered from the individuals themselves. In the laboratory, these measures can be calculated with less bias and tests can be conducted to answer more questions without the problems faced with field data.

This essay describes laboratory experiments that examine the effects of social ability in a market setting. Tests were conducted to determine whether social ability has a significant effect on one's earnings. The results are as expected: social ability has a significant effect upon earnings. How one is rated by others in a social environment affects an individual's earnings in an employment environment. It is therefore important to measure social ability and its direct effect upon earnings. This essay is designed to provide a baseline for further research in this area.

2.2 Experimental Design and Procedure

The experimental design entails two steps. The main objective is to mimic the labor market in this design. In the first part, social ability is induced. The subjects are assigned randomly to two groups: Group A and Group B. Each group consists of an equal number of subjects, whether 8, 9 or 10 individuals. Group A is given more time and a task that gives group members the opportunity to know each other better and be more social. The subjects are able to spend 40 minutes with each other. In the first 10 minutes, each group member shares information regarding their name, major, hobbies and special interests, the state and city they are from, and their goals. With this first part, this design forms an environment for Group A to be more social and Group B does not get that environment. Thus, the difference in each group's earnings in the second part is due to the social environment treatment for Group A members, since there is no other difference in the experimental design for both groups. This gives us the opportunity to measure the effects of being social in terms of earnings.

Next, the subjects spend time working on a puzzle together for 30 minutes. If they are able to complete the puzzle on time, they earn \$100 as a group, so in a group of 10 each subject earns \$10. If they are not able to complete the puzzle on time, then none of the group members earn anything. After completing this task, group members complete the survey (provided in the Appendix) about their group members, rating them in terms of whether they like or dislike them.

The members of Group B spend only a few minutes together, giving them less opportunity to be social. This group is the control group. In this group, each member shares their name, then works individually on a word puzzle, and is administered a survey. The survey does not contain as much information as Group A's survey.

After this first part, all subjects (Group A and Group B) jointly participate in the computerized second part of the experiment, where a buy-and-sell market is formed. All subjects are sellers and each of them attempts to sell one widget. The computer serves as the buyer. In each period, the price and the number of widgets that are bought from the market are determined by the computer, and every subject shares this common information at the beginning of each period. After learning this information, subjects have to decide whether or not they want to sell their widget in that period. If they want to sell their widget, then they are 'in the market', just like for an employee to be in the labor market. The names and groups of those who enter the market are seen by all subjects on the computer screen. The members of Group A have their group members' photographs with them throughout the experiment to help them remember each other. Then, each subject is asked to recommend someone from those who enter the market. The buyer will buy widgets from those sellers who get recommended the most. In this part the subjects can recommend anyone but themselves. Thus, subjects recommend another person whom they think is most valuable compared to others. This is similar to job recommendations in a naturally occurring labor market. By letting them recommend themselves, it would be impossible to measure one's social ability. In this case, each subject has to be perceived "good" by others to be able to earn more.

Based on the recommendations, subjects are ranked and those who are recommended more than others are able to sell their widget. In the case of a tie, the computer chooses the seller randomly. The number of widgets that are bought is determined every period by the computer. After a subject sells her widget, an automatic contract is formed for the rest of the periods. This is again to mimic the contract formed between the employee and the employer in the labor market. That subject earns the same amount of money as if she sold her widget in every period. Subjects know this at the beginning of the experiment since it is included in the instructions and the examples they solve before they begin the experiment. However, if the subject chooses to enter the market again while she has a contract, she incurs a cost that is known by the subject; however, the subject can still keep the old contract if she cannot get a new one. This is analogues to a worker staying with her current employer unless potential job market opportunities entice her to conduct on the job search.

The experiment proceeds for 20 periods. In every period the same choices are made. There are two treatments, experienced and no-experience, and six sessions of each treatment are run. For each session 20 subjects are recruited from the students of the Eller College of Management at the University of Arizona. The subjects are informed that this is a two-day experiment. Those who attended the experiment the first day are asked to come back the second day. All subjects receive a $5 show-up fee for each day.

After they arrive, participants read the subject disclaimer form and their names are entered into the computer. The computer randomly assigns the subjects to Group A and Group B. Group B subjects are then taken into the computer lab where they first state their names then individually solve a word puzzle for the first 30 minutes. Group A members stay in a room where they share information about themselves. They then start doing the puzzle as a team for 30 minutes. Each group has a monitor.

After this task, Group A is taken to the computer room and both groups are administered the survey regarding their group. At the end of the first day, subjects are paid for their session and reminded to come the next day. Some subjects didn't show up the next day. Because of the experimental design, each group should consist of an equal number of subjects. If one group had more, one of the subjects was bumped randomly but was still paid the show-up fee. The second day, the subjects stay in the same group; they are given different puzzles and follow the same procedure. The puzzles were hard enough that none of the groups completed the puzzle even though each member of each group worked hard. This prevented subjects to judge others based on productivity. It was more about how they behaved since they could not complete the puzzle.

The following table is the price and quantity demanded for the experiments given to the subjects at the beginning of each period in the computerized part. In this table, the price and quantity are determined such that the quantity is low at the beginning. Thus, this will increase the difference between those who get the most recommendations and those who do not. Then, the price decreases after period 3 until period 9 to create the largest difference between those who get the average number of recommendations and the most number of recommendations. Then there is an increase in both quantity and price, to make subjects who do not get a contract at the beginning happy to come the next day.

TABLE 2.1 Price and Demand for each Period

Period	Price	Demand	Period	Price	Demand
1	150	2	**11**	125	7
2	130	1	**12**	145	3
3	180	2	**13**	190	4
4	100	1	**14**	115	5
5	120	4	**15**	100	2
6	110	3	**16**	170	2
7	100	4	**17**	130	1
8	105	2	**18**	180	3
9	140	1	**19**	100	4
10	160	5	**20**	200	2

2.3 Tests and Results

First, I wanted to see if Group A members who have better ratings in the surveys earn more than those who have lower ratings. I ran a regression of earnings on ratings using all 53 observations from all 6 sessions run on the second day. For ratings, the standard error is 3.06, the p-value is 0.020 and the coefficient on ratings is 9.98. This result shows that there is a statistically significant positive relation between ratings and earnings of the subjects. This means subjects who are perceived to be “good” during the first part, earned more. Subjects recommended those who have higher social ability i.e. whom they like more during the first part.

Then, I estimated a logit model by adopting the method Eckel and Grossman (1998) used in their paper where they analyzed the outcomes of dictator games. I defined HIGHEARN as an indicator for those who earned higher than the mean earnings (22.66) and SOCIAL as an indicator for those who had higher ratings than the mean ratings (4.129). After running the logit, the variable SOCIAL has a positive coefficient (1.504), the standard error is 2.553 and p-value .0107 with a sample size of 53. Even though this test gives the same results, it helps us see the result that social people earn more, better.

These results show us that how people think about you affect their decision to recommend you or not, which in turn affects the earnings of the subjects. I also wanted to see if this was the case for Group B members. Even if they didn’t have the information about the other subject upon which to base their decision, could it just be based on appearance? For Group B members, the survey results are as expected, the ratings are the same for all group members. Some subjects didn’t fill them out, stating that they didn’t have enough information. Even though a regression cannot be run, the raw data provides enough information that subjects did not complete the surveys just based on appearance. As a result of these findings, it is shown that being social helps people to earn more.

Secondly, I tested to see if the highest earnings of Group A members are more than the highest earnings of Group B members. This is also important, because I wanted to determine whether those who can make good analytical decisions are better off by being in a social environment. Unfortunately, in this case, each experiment is one observation. Thus, with only 6 observations, the difference of means test t-stat is 2.30, and the p-value is 0.0440. Therefore, I can reject the hypothesis that difference of means is zero. Since there are only 6 observations, I am unable to use any alternative methods. The highest earnings of Group A are significantly more than those of Group B. This shows that the people with ability to make good analytical decisions are better off by being social.

Then I wanted to compare two groups. However, in order to do this, I first controlled for those who do not behave rationally in both groups. Behaving rationally means to enter the market when the subject has no contract in hand. If they don't enter the market they have no chance to earn anything while they do not lose anything by entering the market. Thus, those subjects who did not enter the market when they did not have any contract at any period are eliminated. This was necessary, because if Group A had more irrational subjects it would underestimate the effects of being social. This could be due to not understanding the experiment, or just because they were tired and did not want to do anything. The subjects who did not enter the market when they did not have a contract were eliminated. Group A had more subjects eliminated than Group B. From both groups there were a total of 78 observations.

I defined AMOUNT=1 when the earnings were higher than the average earnings of 24.06, which is the mean of all rational subjects' earnings. Then, a logit was run for AMOUNT using GRNUM variable defined as 1 if subjects belong to group A (social group). In this case, the coefficient is 1.707, the standard error is 0.466 and the p-value is 0.079. Thus, we can reject the hypothesis that group category has no effect on the amount being higher than the mean of the subjects' earnings. This is important in order to see if Group B (the control group) has different results than Group A. This shows that the first part where subjects spend time together and do a puzzle affects the earnings.

TABLE 2.2 Tests and Statistics

Test Description	*Statistics*	*p-value*
OLS of Earnings* on RATINGS	9.98 (3.06)	0.020
Logit Analysis of HIGHEARN** on SOCIAL***	1.504 (2.553)	.0107
Test of difference of means for the highest earnings****	2.30	0.0440
Logit Analysis of AMOUNT † and GRNUM †† conditional on behaving rationally	1.707 (.466)	0.079

Where in the above table;

* Dollar amount earned by the subjects.

** HIGHEARN=1 if earnings > 22.66, mean of all the earnings.

*** SOCIAL=1 if subject is Group A member.

**** Each group's mean of highest earnings in all 6 sessions are compared.

† AMOUNT=1 if earnings of rational subjects > 24.06, the mean of the earnings of rational subjects.

†† GRNUM=1 if subjects belong to group A.

‡ Data from the first day's experiments are not used. For subjects, it is not an easy experiment, so the first day is necessary to understand the experiment itself. None of the results were significant. Therefore, no-experience data is not used.

2.4 Summary and Conclusions

In this essay I am seeking to further understand the effects of social ability on one's earnings. I designed experiments to help answer this question. These experiments were conducted in the Economic Science Laboratory at the University of Arizona. Understanding the effects of social ability is becoming more important since the job market is becoming more competitive and time is a scarce resource. These experiments give us preliminary results to further investigate this area.

All these results show that:

1. Within the social environment (Group A treatment) , the earnings of those who are rated higher are more than those who are rated lower.

2.a. Those who make rational decisions pertaining to market entry are better off by being in a social environment.

2.b. The highest earning people are better off by being in a social environment.

However, more testing is still necessary in this area. For future work, additional experiments could be run with different treatments, e.g. forfeiting one's contract when entering the market, being able to recommend one's self, and recommending more than one person but with a ranking or without cost. All these different treatments will help to better understand the effects of social ability in a laboratory environment.

CHAPTER 3. RAIDING AND WAGES

3.1 Introduction

In the competitive labor market, it is becoming more important to consider many different factors that might affect employees' and employers' decisions. In this competitive environment, it is crucial for employers to find new signals with which to distinguish applicants. Economists have investigated many different factors that can affect people's earnings beyond what is considered in standard models (Hamermesh & Biddle, 1994, 1998; Kuhn & Weinberger, 2002). These studies showed that cognitive skills like beauty and leadership are effective in earnings. Another important factor in labor market that has been discussed over the years is "raiding".

In general, "raid" means to be taken over. In the labor market, it is defined as accepting a better job offer while being employed; in essence taken over by another company. Edward Lazear (1986) constructed a model with raiding using a game theory perspective, and showed with simulations that raiding actually increases the expected wage for those raided. Lazear states that many job changes occur without unemployment. In his model, this feature is incorporated into the wage-setting and turnover process. The model implies that the best workers are hired away first. Since job changes and offers are an important component in the identification of worker productivity, there develops a stigma associated with failing to receive outside offers. He also derived interesting results for the labor market, including:

1. The best workers are more likely to be raided. This yields a variation in the Peter Principle: The best workers are stolen away, so those who remain appear incompetent relative to their peers.
2. Wages of workers who receive offers differ from those who do not.
3. Workers who search for jobs during time not worked may actually have lower wages than those who “loaf” during unworked time. A failed search carries worse connotations for the worker’s productivity than not searching at all.

Tranaes (2001) constructed an alternative model and has shown that raiding opportunities affect not only one’s earnings but all labor market outcomes. His model shows that raiding opportunities suggest new implications for unemployment, unemployment compensation, minimum wages, wage taxation and search requirements. Tranaes states that when firms raid, more people are hired through raiding instead of using the more costly process of sorting the good workers from bad workers in the unemployed pool. In his model, raiding increases wages and therefore reduces employment and increases unemployment. When unemployment increases and wages are high, firms will start choosing away workers from the unemployed pool. In equilibrium some highly qualified workers are unemployed. They would prefer to work, even for less than the going wage rate, but job offers are not forthcoming because no firm is willing to pay the costs of sorting highly qualified workers out from the less able unemployed, given the raiding opportunities of the firm’s competitors. Raiding also increases the reservation wage for employed workers and decreases it for unemployed workers. Simon and Warner (1992) have shown that employees hired through referrals earn higher initial wages, experience lower wage growth, and stay on the job longer. They also found substantial support for their theory from the 1972 Survey of National and Social Scientists and Engineers. Referrals form an important base for raiding. Another important study by Howitt and McAfee (1987) constructs a model that incorporates different market structures, including raiding. They also found that unemployment increases when firms can recruit from other firms.

While Lazear's (1986) paper provides a baseline for understanding the effects of raiding on one's earnings, Guasch and Sobel (1983) study the strategic production of skills within the firm and characterize when a firm should train its own employees and when it should bid for workers trained by others. Laing (1994) studies the optimal contract between a firm and a worker under the influence of an external spot market. He also found that retained workers receive "high" spot market wage offers that the firm must match to prevent raids and laid-off workers receive "low" spot market wage offers when there is the possibility of raiding.

Lazear (1986) also defines unemployed job search as not being raided from unemployment and shows that unemployed job search is worse than not searching at all. Blau (1992) studies the job search activities of employed and unemployed job seekers using self-reported data from a 1980 survey and shows that unemployed job search is less productive. There are numerous other studies about job search. (e.g., Reid, 1972; Blau & Robins, 1990) Until Lazear (1986), job search was not thought of as being related to the probability of raiding.

All these theoretical models show that raiding affects the labor market. However, despite the theoretical insertion of raiding into job market models, there has been very little done in terms of statistical testing about whether raiding directly affects earnings or not.

In this essay, the relationships between wages and raiding are examined using data from the 1979 National Longitudinal Survey of Youth (NLSY). The relationships between raiding and hourly wages, the number of hours worked, earnings, annual income and wage growth are established.

3.2 Empirical Model

I plan to examine empirical relationships between staying with the same firm over an extended period and various labor market measures including earnings, hours, hourly rate and annual income. In addition, I will examine the relationships between earnings, hours, hourly rate, annual income, raiding and job search while unemployed in the context of a standard reduced-from model. Each model takes the following form.

$$DV_{it} = \alpha_{0it} + \alpha_{1it}\, RAID_{it} + \alpha_{2it}\, X_{it} + r_i + \varepsilon_{it}. \tag{3.1}$$

I estimate the model for several dependent variables DV_{it} for individual i in year t. They include the log of hourly earnings (LHRATE), the log of annual hours worked (LHOURS), the log of annual earnings (LERNS), the log of income (LINCOME) and the change in log income (WG). The $RAID_{it}$ variable is defined as workers who were employed before their current job and were not looking for a job before starting their current job. I also run the model by replacing RAID with SAME, which refers to workers who have been working for the same employer for an extended period of time. Another model is estimated where RAID is replaced with LFWORK which is the measure for those who search while unemployed before starting their current job. This measure is used to test the failed search result Lazear (1986) derived, because the unemployed search is a case of failed search i.e. failed to be raided from unemployment as Lazear stated. Unemployed search is also measured easily with the data. This is designed to capture Lazear's concept of people who are not raided from unemployment for sometime.

According to the Lazear model, the coefficient of RAID will be positive, while the coefficient of SAME and the coefficient of LFWORK will be negative. The vector X_{it} includes a series of control variables, including experience which is the actual market experience and experience squared, industry dummies, and education. The control variables might not measure all of the relevant characteristics of the worker that will determine their earnings or hours. To control for some of these relevant individual factors, represented by r_i, I estimate the model in a random effects framework and also in a fixed-effects framework. The random effects model in this essay controls for factors that are largely time-invariant although subject to stochastic shocks. The fixed effects framework controls for time-invariant factors that vary across individuals. I can run the random effects model with several years of data when using the SAME specification. On the other hand, the RAID and LFWORK variable can only be computed for two years, 1994 and 1996. To eliminate the r_i parameter in the RAID specification, I run the model with all of the variables first as OLS in 1994 and then as the differences between 1994 and 1996. When the dependent variable is the change in log income, the model is run as fixed effects, because while estimating random effects, the estimated variance of the error for random effects is not positive.

3.3 Data

For the random effects and fixed effects models, the NLSY 79 Cohort Work History Data are used from years 1990, 1992, 1994, 1996, 1998, and 2000. The sample consists of the same group, white males in each year. I focus on this group to avoid the effects of children and home duties that often influence the wage and employment decisions of women. To also avoid racial and ethnic influences, only white males are considered. There are 1164 observations for the hourly rate, hours worked and wage growth models. The same sample is used in all random effects and fixed effects regressions. Since the raiding and search data are available only for 1994 and 1996, the random effects estimation does not provide valid results, except for the wage growth model. For the OLS models, including the model of differences, I used the NLSY 79 Cohort Work History Data from 1994. Again, my sample consists of white male subjects. I have 1364 observations for the wage rate and hours worked models. The same sample is used in all OLS regressions and the difference estimation. Data used in these regression models are explained in Table 3.1.

In the LHRATE variable, respondents who reported an hourly rate (expressed in terms of cents per hour) of less than $1.00 are excluded. The data were collected every year until 1994, and then every two years thereafter. In order to make the analysis consistent, all data were taken from even years only then the log is taken to create LHRATE.

For LHOURS, the number of hours worked is reported as weekly data. Respondents reporting negative hours worked were excluded. The NLSY79 created annualized data by totaling the weekly data that is collected from the respondents. For consistency, hours worked were summed over two-year periods before the log was taken when LHOURS data are created. Hours worked were summed not averaged, because by averaging some effects of being unemployed, changing employers and getting raided could be lost. The log earnings for a two-year period variable (LERNS) is the sum of LHOURS and LHRATE variables.

The SAME variable is a dummy variable created for workers who had the same employer consecutively for each two-year period. According to the theoretical model, changing jobs can yield a higher wage. Even though this dummy does not take into account the effect of changing the job within the same employer, it does not overestimate the effect, and rather underestimates it. Since, those who stay with the same employer could start earning more by changing their jobs. Better measurement for this purpose could not be found in NLSY data.

Subjects are asked two important questions in 1994 and in 1996: 1) Whether they were employed before starting their current job, and 2) Whether they were looking for jobs before starting their current job. If they answer "Yes" to the first question in 1994, then a dummy is created as EMP = 1, and if they answer "Yes" to the second question, then another dummy is created as SEARCH = 1. After these dummies are created, raiding is defined as those who are employed and not looking for a job before they start their current job. Thus the dummy RAID = 1 when EMP = 1 and SEARCH = 0. Searching for a job is defined as those who are looking for a job during time not worked. Thus, LFWORK dummy is also created when EMP = 0 and SEARCH = 1.

EXP is normalized actual market experience obtained by first totaling the hours that the respondents work each week during the two-year period and then dividing the total hours worked by 2,000, assuming two 50-week years and 40 hours per week.

INCOME is the total annual earnings of the respondents received from wages. The respondents answered the question about their total income from wages for each year and just the even year observations are used. This should not be confused with earnings, since the earnings variable has been calculated by using the reported hourly rate and the number of hours worked hence not annual. This is a measure for annual earnings. The rest of the data is explained in Table3.1.

3.4 Empirical Results

The sample used for random effects and fixed effects models consists of white males who have an hourly wage higher than $1.00, annual income higher than $10.00 and who have positive hours worked. The panel data set consists of six observation years for each person (1990, 1992, 1994, 1996, 1998, and 2000). In the NLSY79 after 1994, data were collected every two years, so for consistency, data before 1994 are also used only every two years. The Breusch-Pagan Lagrange Multiplier (BP-LM) test rejects OLS in favor of random effects (RE) for the first three estimations where DV_{it} = LHOURS , LHRATE and LERNS and instead of RAID, SAME variable is used. In these estimations, the coefficients for SAME are negative and statistically significant as predicted. The results are reported in Table 3.2 for Random Effects and Table 3.3 for Fixed Effects.

In the wage-rate model (LHRATE), the coefficient for SAME is positive but statistically not significant in both the random and fixed effects models. In the number of hours model (LHOURS), the coefficient for SAME is - 0.138 for RE, - 0.086 for FE, and statistically significant. Therefore, those workers who stay at the same job work significantly less than others. This is not surprising: in the first year on the job, employees have to prove themselves more. They also need to put in more time to meet the job's learning curve. This supports Lazear in a way as he states that those workers who stay within the same firm are less productive. However, this doesn't help us understand whether those who are not good workers are the ones who stay or not. Then, the log annual earnings model is estimated (LERNS). The coefficient of SAME is – 0.115 for RE, - 0.08 for FE and statistically significant. These results are likely due to working less time.

Therefore, the effects of staying at the same job on income from wages are estimated with log of income (LINCOME). Again, the BP-LM test rejects OLS in favor of RE and FE, and the coefficient of SAME is -0.063 for RE and statistically significant in the RE model. However, in the FE model, the coefficient is not statistically significant. These results are reported in Table 3.4. Thus, the Hausman (1978) test is done for superiority of random effects versus fixed effects. The Hausman is 16.15 and the p-value is .30 for the null hypothesis that the fixed effects model is appropriate. Thus we fail to reject that FE is more appropriate. These results are reported in Table 3.4. By the estimation of the wage-growth equation, no significant results have been found. These results are also reported in Table 3.4. Random effects could not be estimated because the estimated variance of the error for random effects is not positive. Only the fixed effects model is estimated but there are no significant results. The results are consistent with the findings of Lazear (1986) that those who stay on the same job are less productive workers, as well as the findings of Abraham and Farber (1987). Abraham and Farber (1987) state that the measured positive cross-sectional return to seniority is largely a statistical artifact due to the correlation of seniority with an omitted variable representing the quality of the worker, job or worker-employer match.

The sample used for the rest of the equations also consists of white males, who have an hourly wage higher than \$1.00, an income higher than \$10.00 and who have positive hours worked in 1994.Since the data used to measure raiding are only available for 1994 and 1996, the first estimation is OLS for the cross-section 1994 and then the difference between 1994 and 1996 for each variable is measured and estimated. Since some were unemployed between the two-year period, difference of EXP and EXPSQ are also included.

As expected, the results of OLS for 1994, in the hourly earnings model (LHRATE), the coefficient for RAID is 0.117 and statistically significant. Thus, the effect of getting raided increases one's hourly wages by roughly 11.7 percent. In the number of hours model (LHOURS), the coefficient for RAID is also positive, 0.121 and statistically significant. Therefore, those workers who are raided work significantly more hours than others. Then, the log annual earnings model is estimated (LERNS). The coefficient of RAID is 0.238 and statistically significant. The results are reported in Table 3.5. These results are consistent with Lazear's findings that raided workers earn higher earnings and work more.

The effects of raiding on income from wages are also estimated with the log income model (LINCOME). Again, the coefficient of RAID is 0.153 and statistically significant as expected. These results are also reported in Table 3.5. When the wage-growth equation (change in LINCOME) is estimated, no statistically significant results are found. The random effects again could not be estimated. Also, the fixed effects can not be estimated since RAID is time-invariant in the WG model. In this case, the variable RAID is just for 1994 and the rest of the data are for all the years (1990, 1992, 1994, 1996, 1998, and 2000). These results are reported in Table 3.7.

To be able to see the effects of raiding controlling for time-invariant individual characteristics, the differences between years 1994 and 1996 in all variables are estimated. In these estimations, for the log of earnings (LERNS) model, the coefficient for difference of RAID is 0.089 and statistically significant. However, for LHOURS, LHRATE and LINCOME no statistically significant coefficients are found. The results are reported in Table 3.6. Over all, the results for LERNS provide strong support that raiding is important in determining earnings and does directly affect one's earnings. Since no statistically significant coefficient found for LHOURS, it is shown that raiding does not increase earnings by increasing the worked hours but directly. However, for the other measure of annual earnings that is LINCOME and LHRATE did not confirm Lazear's theory.

To test another conclusion derived in Lazear's paper which is the effects of search when not employed on earnings, again the models where DV_{it} = LHOURS , LHRATE, LERNS, LINCOME and the change in LINCOME (WG) are estimated and instead of RAID, the looking for work (LFWORK) variable is used. The results for these estimations are reported in Table 8 and for WG are reported in Table 3.7. It is expected that during unemployment, search has a negative relationship with earnings. As Lazear stated, workers who search for jobs during unemployment may actually have lower wages than those who "loaf" during unworked time. A failed search carries worse connotations for the worker's productivity than not searching at all. As expected, in the hourly earnings model (LHRATE), the coefficient for LFWORK is – 0.083 and statistically significant. This shows Lazear's findings are valid. In the number of hours model (LHOURS), the coefficient for LFWORK is – 0.144 and statistically significant. This is not a surprising result, because respondents are unemployed before their current job. Then, the log annual earnings model is estimated (LERNS). The coefficient of LFWORK is -.227 and statistically significant. These results are again consistent with Lazear's findings.

The effects of search during the time not worked on income from wages are again estimated using the log of income model (LINCOME). Consistent with the above results, the coefficient of LFWORK is - 0.144 and statistically significant. All these results for LFWORK are reported in Table 3.8. When the wage-growth equation is estimated, no statistically significant results are found. In this case, the variable LFWORK is just for 1994 and the rest of the data are for all the years (1990, 1992, 1994, 1996, 1998, and 2000). This is considered in order to see the effects of search during unemployed time on the pattern of wage growth. However, random effects could not be estimated again because the estimated variance of the error for random effects is not positive. The results of wage growth are reported in Table 3.7.

Again, to see the estimations without uncontrolled individual characteristics, the differences of all variables between the years 1996 and 1994 is estimated. In these estimations, in LERNS, LHOURS and LINCOME models, the coefficients for the difference of LFWORK is – 0.071, - 0.066 and - 0.094, statistically significant and as expected. However, no significant results are found for LHRATE model. These results are reported in Table 3.9.

Since all wage growth equations give statistically insignificant results, instead of defining wage growth based on total income earned from wages, I also defined wage growth based on hourly wages. The results are still statistically insignificant and again the random effects model could not be estimated.

3.5 Summary and Conclusions

In this essay I examine the following findings of Lazear (1986) are also consistent with NLSY 79 Cohort Work History Data:

1. The best workers are more likely to be raided. This yields a variation in Peter Principle: The best workers are stolen away, so those who remain appear incompetent relative to their peers.
2. Wages of workers who receive offers differ from those who do not.
3. Workers who search for jobs during time not worked may actually have lower wages than those who “loaf” during unworked time. A failed search carries worse connotations for the worker’s productivity than not searching at all.

By using data for white males from 1990–2000, I created a sample used in random effects regressions of hourly rate, number of hours, and total income from wages. The earnings variable is created by using hourly rate and number of hours. Wage growth is created by using total income from wages. I used random effects in the panel data sample regressions since the BP-LM test rejects OLS in favor of random effects, except in the case of the wage growth models. I found that Lazear’s findings are supported in some of these regressions about job seniority. The coefficient for staying in the same job is negative and statistically significant in the earnings model, negative and statistically significant in the number of hours worked model, and negative and significant in the income model. However, for the income model the fixed effects model is valid by the

Hausman test. Thus, only the earnings model is supportive of Lazear's theory. No significant results were found for wage growth models and the hourly earnings.

I used the same sample consisting of white males but for only one year, 1994, to see the effects of raiding and job search during time not worked. OLS estimation for hourly earnings, number of hours, earnings and total income from wages showed that raiding has a positive effect on earnings, and hourly rate, income from wages, and job search during time not worked have a negative effect on earnings. All of these results are consistent with the theoretical findings. To see the effects of raiding by controlling for the time-invariant individual characteristics, another set of OLS ran by using the difference of each variable. Some of the results are consistent with the theory. In these estimations, for the earnings model, the coefficient for difference of RAID is positive and statistically significant. However, for number of hours worked, hourly earnings and annual income, no statistically significant coefficients are found. For number of hours worked, hourly earnings and annual income, the coefficients for the difference of LFWORK are consistent with the theory. This is very important; researchers have been trying to understand other determinants of earnings, theoretically and empirically. When the effect of being raided is understood, most of cognitive skills can be viewed important because they increase the probability of being recognized by others and therefore getting raided. Since the direct effect of raiding on earnings is showed in this essay, most of cognitive skills like social ability, leadership, and social network can be indirectly effective on earnings through raiding rather than increasing the earnings directly as believed.

In today's more complicated labor market, it is important to understand if the theory is valid in the real job market. For years it has been believed that job seniority increased earnings. As Lazear stated, job seniority is actually a failure to be raided, which signals the lower quality of the worker. It is also the case that an unemployed search is worse than not searching because it signals a failure to be raided from unemployment. Therefore, raiding is an important signal about the worker's quality. Understanding raiding will help understand the effects of cognitive skills and search. There is a growing volume of literature on this issue, and finding support from data is crucial. Even though further research is needed, the results of this essay provide some support from the NLSY 79 cohort and help to understand the effects of raiding.

TABLE 3.1 Variables

LHRATE	Log of hourly rate for 1990,1992,1994,1996,1998,2000.
LHOURS	Log of number of hours worked every two years.
LERNS	Log of earnings created by LHOURS + LHRATE ; since earnings is equal to hours worked times hourly wages.
SAME	Dummy variable for having the same employer the following observation year (after two years)
DIFF	Dummy variable for not having the same employer the following observation year (after two years), left out for regressions.
IND	Industry dummies
AGRI	Agriculture, forestry and fisheries
MINE	Mining
CONSTR	Construction
MANUF	Manufacturing
PUBUT	Transportation, communication and public utilities
TRADE	Wholesale and retail trade
FINANCE	Finance, insurance and real estate
SERVICE	Business, repair and personal service
ENTER	Entertainment and recreation services
PROFSERV	Professional and related services
PA	Public administration, left out for the regressions.
EXP	Total experience, normalized; divided by 4000, assuming there are 50 work weeks per year and 40 hours per week over 2-period.
EXPSQ	Experience square
EDUC	Education
EMP	Dummy variable for those who were employed before they started their current jobs.
NOEMP	Dummy variable for those who were not employed before they started their current jobs (Left out for regressions)
SEARCH	Dummy variable for those who were looking for a job before they started their current jobs.
NOSEARCH	Dummy variable for those who were not looking for a job before they started their current jobs.(Left out for regressions)
RAID	Dummy variable for those EMP=1 and SEARCH=0.
NORAID	Dummy variable for those who are not raided.(Left out for regressions)
LFWORK	Dummy variable for those EMP=0 and SEARCH=1

TABLE 3.1-Cont Variables

NLFWORK	Dummy variable for those who do not look for work or not employed. (Left out for regressions)
INCOME	Total earnings from wages.
LINCOME	Log of income.
WG	Wage growth over two years i.e. difference of the log wage in two consecutive observation years.
DIFFRAID	Difference of RAID dummy between 1996 and 1994.
DIFFEDUC	Difference of EDUC between 1996 and 1994.
DIFFAGRI	Difference of AGRI dummy between 1996 and 1994.
DIFFMINE	Difference of MINE dummy between 1996 and 1994.
DIFFCONS	Difference of CONSTR dummy between 1996 and 1994.
DIFFMAN	Difference of MANUF dummy between 1996 and 1994.
DIFFPUB	Difference of PUBUT dummy between 1996 and 1994.
DIFFTRA	Difference of TRADE dummy between 1996 and 1994.
DIFFFIN	Difference of FINANCE dummy between 1996 and 1994.
DIFFSER	Difference of SERVICE dummy between 1996 and 1994.
DIFFENTM	Difference of ENTER dummy between 1996 and 1994.
DIFFPSER	Difference of PROFSERV dummy between 1996 and 1994.
DIFFEXP	Difference of EXP between 1996 and 1994.
DIFFEXPS	Difference of EXPSQ between 1996 and 1994.
DIFFLFW	Difference of LFWORK dummy between 1996 and 1994.

TABLE 3.2 Random Effects of Earnings, Hourly Rate, Hours Worked

	LERNS-RE		LHOURS-RE		LHRATE-RE	
	coefficient	s.errors	coefficient	s.errors	coefficient	s.errors
Constant	8.092	.222	7.306	.152	.997	.152
SAME	-.115	.045	-0.138	.033	.012	.027
EDUC	.111	.012	.024	$.768\text{x}10^{-2}$	.073	$.888\text{x}10^{-2}$
AGRI	.043	.149	.13	.109	-.117	.097
MINE	.46	.283	.103	.218	.318	.182
CONSTR	.253	.116	$-.5\text{x}10^{-2}$	.086	.168	.076
MANUF	.033	.112	.115	.084	-.157	.073
PUBUT	.064	.127	.058	.095	-.036	.083
TRADE	-.025	.111	.096	.082	-.162	.072
FINANCE	.142	.153	.038	.113	.048	.1
SERVICE	-.023	.115	.022	.087	-.089	.075
ENTER	-.124	.185	-.034	.142	-.131	.119
PROFSER	-.266	.120	-.096	.089	-.216	.078
EXP	.194	.031	.113	.023	.082	.021
EXPSQ	$-.4\text{x}10^{-2}$	$.21\text{x}10^{-2}$	$-.27\text{x}10^{-2}$	$.15\text{x}10^{-2}$	$-.12\text{x}10^{-2}$	$.136\text{x}10^{-2}$
R^2	.2757		.1500		.2443	
NOB	1164		1164		1164	

TABLE 3.3 Fixed Effects for Earnings, Hourly Rate, and Hours Worked

	LERNS-FE		LHOURS-FE		LHRATE-FE	
	coefficient	s.errors	coefficient	s.errors	coefficient	s.errors
SAME	-.080	.044	-.086	.036	$.61\text{x}10^{-2}$	.027
EDUC	.101	.055	.059	.046	.047	.034
AGRI	.242	.166	.285	.136	-.043	.102
MINE	.455	.302	.102	.248	.352	.186
CONSTR	.168	.135	.16	.112	$.83\text{x}10^{-2}$	.084
MANUF	.123	.123	.272	.101	-.15	.076
PUBUT	.018	.144	.114	.119	-.097	.089
TRADE	.084	.122	.21	.101	-.126	.076
FINANCE	.042	.181	.137	.149	-.095	.111
SERVICE	.026	.127	.112	.105	-.086	.078
ENTER	-.228	.207	.026	.17	-.254	.127
PROFSERV	-.121	.133	.088	.11	-.209	.082
EXP	.195	.035	.101	.029	.094	.022
EXPSQ	$-.51\text{x}10^{-2}$	$.23\text{x}10^{-2}$	$-.377\text{x}10^{-2}$	$.191\text{x}10^{-2}$	$-.13\text{x}10^{-2}$	$.142\text{x}10^{-2}$
R^2	.5749		.3436		.6606	
NOB	1164		1164		1164	

TABLE 3.4 Results for the LINCOME Model of the SAME variable

	LINCOME-RE		WG S (FE)		LINCOME-FE	
	coefficient	s. errors	coefficient	s. errors	coefficient	s. errors
Constant	7.51	.24	-	-	-	-
SAME	-.063	.037	.13	.164	-.049	.408
EDUC	.117	.015	.179	.083	.093	.052
AGRI	-.1	.135	.064	.63	-.021	.154
MINE	.293	.248	.263	.954	.294	.269
CONSTR	.175	.111	.565	.472	.174	.129
MANUF	-.014	.103	.288	.434	.026	.116
PUBUT	.211	.119	.664	.506	.221	.134
TRADE	.019	.102	.287	.427	.071	.115
FINANCE	.067	.141	.34	.6	.054	.162
SERVICE	-.186	.107	-.181	.446	-.164	.121
ENTER	.052	.174	.061	.731	.133	.193
PROFSER	-.11	.11	-.4	.46	-.029	.123
EXP	.152	.028	-.045	.048	.151	.0318
EXPSQ	$-.294\text{x}10^{-2}$	$.187\text{x}10^{-2}$	-	-	$-.307\text{x}10^{-2}$	$.21\text{x}10^{-2}$
R^2	.2805		.2473		.6467	
NOB	1085		833		1085	

TABLE 3.5 Results for the OLS models of the RAID

	LERNS		LHRATE	
	Coef.	s.errors	Coef.	s.errors
Constant	7.547	.164	.659	.111
RAID	.238	.054	.117	.037
EDUC	.129	$.84 \times 10^{-2}$	.093	$.57 \times 10^{-2}$
AGRI	-.349	.128	-.2	.087
MINE	-.081	.283	.178	.193
CONSTR	-.139	.084	.026	.057
MANUF	-.157	.078	-.104	.053
PUBUT	.028	.092	.017	.063
TRADE	-.325	.082	-.233	.056
FINANCE	.025	.128	.121	.087
SERVICE	-.199	.087	-.139	.059
ENTER	-.474	.237	-.268	.162
PROFSERV	-.374	.085	-.184	.058
EXP	.344	.033	.132	.023
EXPSQ	-.013	$.26 \times 10^{-2}$	$-.6 \times 10^{-2}$	$.18 \times 10^{-2}$
R^2	.372		.2646	
NOB	1364		1364	

TABLE 3.5-Cont Results for the OLS models of the RAID

	LHOURS		LINCOME	
	Coef.	s.errors	Coef.	s.errors
Constant	6.88	.113	7.22	.167
RAID	.121	.037	.153	.049
EDUC	.036	$.58\text{x}10^{-2}$	.122	$.78\text{x}10^{-2}$
AGRI	-.148	.088	-.546	.126
MINE	-.099	.195	-.266	.242
CONSTR	-.165	.058	-.178	.08
MANUF	-.053	.054	-.015	.074
PUBUT	.011	.064	.029	.086
TRADE	-.093	.057	-.183	.078
FINANCE	-.096	.088	.149	.121
SERVICE	-.06	.06	-.23	.083
ENTER	-.206	.164	-.163	.217
PROFSERV	-.19	.059	-.255	.08
EXP	.212	.023	.252	.035
EXPSQ	$-.76\text{x}10^{-2}$	$.18\text{x}10^{-2}$	$-.9\text{x}10^{-2}$	$.26\text{x}10^{-2}$
R^2	.274		.3206	
NOB	1364		1294	

TABLE 3.6 Results for Estimation of the difference in all variables and RAID

	LERNS		LHRATE	
	Coef.	s.errors	Coef.	s.errors
Constant	-.02	.023	.095	.017
DIFFRAID	.089	.05	.039	.036
DIFFEDUC	-.088	.067	-.034	.047
DIFFAGRI	-.433	.148	.047	.1
DIFFMINE	.221	.243	$.476 \times 10^{-2}$	.172
DIFFCONS	.111	.102	$-.72 \times 10^{-2}$	.072
DIFFMAN	.144	.089	.042	.063
DIFFPUB	-.071	.119	$-.29 \times 10^{-2}$	.084
DIFFTRA	.117	.097	.074	.069
DIFFFIN	.216	.149	.1	.105
DIFFSER	.094	.096	.081	.069
DIFFENTM	$.98 \times 10^{-2}$	.214	-.093	.151
DIFFPSER	.23	.099	.026	.07
DIFFEXP	2.46	.145	.228	.103
DIFFEXPS	-.698	.069	-.115	.049
R^2	.4331		.0196	
NOB	736		736	

TABLE 3.6-Cont Results for the difference of RAID

	LHOURS		LINCOME	
	Coef.	s.errors	Coef.	s.errors
Constant	-.114	.018	.105	.025
DIFFRAID	.039	.038	.049	.051
DIFFEDUC	-.054	.052	.032	.069
DIFFAGRI	-.357	.105	-.029	.176
DIFFMINE	.167	.179	.38	.234
DIFFCONS	.11	.078	.077	.121
DIFFMAN	.079	.068	.036	.105
DIFFPUB	-.084	.09	$.93\text{x}10^{-2}$	.135
DIFFTRA	.037	.073	.057	.112
DIFFFIN	.1	.111	.03	.163
DIFFSER	$.21\text{x}10^{-2}$	.074	.183	.113
DIFFENTM	.079	.161	-.098	.231
DIFFPSER	.23	.074	.142	.109
DIFFEXP	2.29	.11	1.21	.19
DIFFEXPS	-.612	.052	-.289	.086
R^2	.5423		.1564	
NOB	792		647	

TABLE 3.7 Results for the Wage Growth models of RAID and LFWORK

	WGRaid(OLS)		WGLFW (OLS)	
	Coefficient	s.errors	coefficient	s.errors
Constant	1.55	.517	.032	.202
LFWORK	-	-	.101	.132
RAID	-.135	.193	-	-
EDUC	.029	.028	.03	.028
AGRI	-.201	.44	-.201	.44
MINE	-.222	.753	-.024	.752
CONSTR	$.83 \times 10^{-2}$	.329	-.011	.33
MANUF	.088	.321	.079	.321
PUBUT	.13	.363	.118	.364
TRADE	-.063	.317	-.059	.316
FINANCE	-.245	.418	-.206	.417
SERVICE	-.177	.335	-.176	.336
ENTER	.086	.57	.049	.568
PROFSERV	.062	.342	.055	.343
EXP	-.048	.025	-.047	.025
R^2	.0109		.011	
NOB	833		833	

TABLE 3.8 Results for the OLS models of the LFWORK

	LERNS		LHRATE	
	Coef.	s.errors	Coef.	s.errors
Constant	7.704	.166	.715	.114
LFWORK	-.227	.041	-.083	.028
EDUC	.128	$.84 \times 10^{-2}$	.093	$.57 \times 10^{-2}$
AGRI	-.327	.127	-.191	.087
MINE	-.04	.281	.047	.192
CONSTR	-.116	.084	.037	.057
MANUF	-.148	.078	-.099	.053
PUBUT	.023	.092	.018	.063
TRADE	-.309	.082	-.226	.056
FINANCE	.017	.127	.122	.087
SERVICE	-.173	.086	-.126	.059
ENTER	-.399	.237	-.237	.162
PROFSERV	-.375	.086	-.183	.058
EXP	.345	.033	.132	.023
EXPSQ	-.014	$.26 \times 10^{-2}$	$-.58 \times 10^{-2}$	$.18 \times 10^{-2}$
R^2	.3773		.2639	
NOB	1364		1364	

TABLE 3.8-Cont Results for the OLS models of the LFWORK

	LHOURS		LINCOME	
	Coef.	s.errors	Coef.	s.errors
Constant	6.989	.114	7.332	.169
LFWORK	-.144	.028	-.144	.038
EDUC	.035	$.6x10^{-2}$	.122	$.78x10^{-2}$
AGRI	-.135	.087	-.537	.126
MINE	-.087	.193	-.252	.241
CONSTR	-.153	.058	-.163	.08
MANUF	-.048	.054	-.012	.078
PUBUT	$.51x10^{-2}$	.063	.026	.086
TRADE	-.084	.056	-.176	.078
FINANCE	-.105	.088	.144	.121
SERVICE	-.047	.06	-.212	.082
ENTER	-.162	.163	-.113	.217
PROFSERV	-.192	.059	-.253	.08
EXP	.212	.023	.251	.035
EXPSQ	$-.79x10^{-2}$	$.2x10^{-2}$	$-.923x10^{-2}$	$.26x10^{-2}$
R^2	.2825		.323	
NOB	1364		1294	

TABLE 3.9 Results for Estimation of the difference in all variables and LFWORK

	LERNS		LHRATE	
	Coef.	s.errors	Coef.	s.errors
Constant	-.023	.023	.096	.017
DIFFLFW	-.071	.038	$.57 \times 10^{-2}$	.027
DIFFEDUC	-.087	.067	-.033	.047
DIFFAGRI	-.434	.148	.044	.105
DIFFMINE	.205	.241	-.151	.171
DIFFCONS	.103	.102	$-.69 \times 10^{-2}$	.072
DIFFMAN	.14	.089	.044	.063
DIFFPUB	-.08	.119	$-.83 \times 10^{-2}$	.084
DIFFTRA	.11	.098	.078	.069
DIFFFIN	.216	.149	.102	.106
DIFFSER	.079	.097	.081	.068
DIFFENTM	$-.4 \times 10^{-3}$	.214	-.093	.152
DIFFPSER	.224	.099	.025	.07
DIFFEXP	2.44	.145	.226	.103
DIFFEXPS	-.689	.069	-.113	.049
R^2	.4334		.0179	
NOB	736		736	

TABLE 3.9-Cont Results for the estimation of difference LFWORK

	LHOURS		LINCOME	
	Coef.	s.errors	Coef.	s.errors
Constant	-.119	.018	.101	.025
DIFFLFW	-.066	.028	-.094	.039
DIFFEDUC	-.053	.052	.032	.069
DIFFAGRI	-.358	.105	-.015	.175
DIFFMINE	.173	.178	.389	.233
DIFFCONS	.105	.078	.071	.12
DIFFMAN	.075	.068	.028	.105
DIFFPUB	-.086	.09	$.45 \times 10^{-2}$	.135
DIFFTRA	.032	.733	.045	.112
DIFFFIN	.103	.111	.034	.162
DIFFSER	$-.83 \times 10^{-2}$	.073	.163	.113
DIFFENTM	.078	.161	-.092	.23
DIFFPSER	.229	.074	.138	.109
DIFFEXP	2.28	.11	1.19	.189
DIFFEXPS	-.61	.052	-.285	.085
R^2	.5449		.1628	
NOB	792		647	

APPENDIX A: HAUSMAN AND TAYLOR ESTIMATOR

Because I suspected that OUT (social ability measure) would turn out to be endogenous in the Random Effects Model, I used the Hausman and Taylor (1981) Estimator. There are weak positive results for LERNS, but not significant results for LHOURS and LHRATE. Results are reported in Table 5 at the end of this section.

The procedure for Hausman and Taylor is illustrated in the following model:

$$y_{it} = \beta_1^{'} x_{1it} + \beta_2^{'} x_{2it} + \gamma_1^{'} f_{1i} + \gamma_2^{'} f_{2i} + \varepsilon_{it} + u_{it} \qquad \text{A-1}$$

Where,

$$\beta = (\beta_1^{'} \beta_2^{'})^{'} \quad \text{and} \quad \gamma = (\gamma_1^{'} \gamma_2^{'})^{'} \qquad \text{A-2}$$

And,

$$E[u_i] = 0, Var[u_i] = \sigma_u^{2}, Cov[\varepsilon_{it}, u_i] = 0 \qquad \text{A-3}$$

$$Var[\varepsilon_{it} + u_i] = \sigma^2 = \sigma_\varepsilon^{2} + \sigma_u^{2}$$
$$Corr[\varepsilon_{it} + u_i, \varepsilon_{is} + u_i] = \rho = \frac{\sigma_u^{2}}{\sigma^2} \qquad \text{A-4}$$

There are four sets of variables in the model:

	Uncorrelated with u_i	Correlated with u_i
Time varying	$\mathbf{x}_{1it}$ is KX_1 variables	$\mathbf{x}_{2it}$ is KX_2 variables
Time invariant	$\mathbf{f}_{1i}$ is KF_1 variables	$\mathbf{f}_{2i}$ is KF_2 variables

In the models estimated, the variables are as follows:

	Uncorrelated with u_i	Correlated with u_i
Time varying	SAME, IND, EXP, EXPSQ, EDUC	NONE
Time invariant	Constant	OUT

where y is LHRATE or LERNS or LHOURS depending on the model.

The strategy for estimation is based on the following logic. First, by taking deviations from group means, we find that:

$$y_{it} = \beta_1^{'}\left(x_{1it} - \bar{x}_{1i}\right) + \beta_2^{'}\left(x_{2it} - \bar{x}_{2i}\right) + \varepsilon_{it} - \bar{\varepsilon}_i \qquad \text{A-5}$$

which implies that **β** can be consistently estimated by least squares, in spite of the correlation between $\mathbf{x_2}$ and u. This is the familiar fixed effects estimator. Now, in the original model, Hausman and Taylor showed that the group mean deviations can be used as (KX_1 +KX_2) instrumental variables for estimation of (**β**,**γ**). Since, $\mathbf{f}_1$ is uncorrelated with the disturbances; it can likewise serve as a set of KF_1 instrumental variables. That leaves a need for KF_2 instrumental variables. The authors show that the group means for $\mathbf{x_1}$ can serve as these remaining instruments, and the model will be identified so long as KX_1 is greater than or equal to KF_2.

The authors propose the following steps:

Step 1. Use consistent but inefficient estimators of **β** and **γ** to estimate the variance components.

Step 2. Use weighted FGLS with instrumental variables to take full advantage of the known information about the variances at a second step.

The specific procedure is as follows.

Step 1. Obtain the fixed effects estimator of $\beta = (\beta_1{}' \beta_2{}')'$ based on $\mathbf{x_1}$ and $\mathbf{x_2}$. The residual variance estimator from this step is a consistent estimator of σ_ε^2.

Step 2. From the within groups residuals from the regression in step 1, e_{it}, stack the group means of these residuals in a full sample length data vector. Thus, $e_{it}^* = \bar{e}_i$, t = 1, …,T_i, i = 1,…, N. These group means are used as the dependent variable in a two stage least-squares regression on $\mathbf{f_1}$ and $\mathbf{f_2}$ with instrumental variables $\mathbf{f_1}$ and $\mathbf{x_1}$. (Note the identification requirement that KX_1, the number of columns in $\mathbf{x_1}$, be at least as large as KF_2, the number of columns in $\mathbf{f_2}$.) This provides a consistent estimator of γ. The residual variance in this regression is a consistent estimator of

$\sigma^{*2} = \sigma_u{}^2 + p\lim(\frac{1}{N})\sum_i \frac{1}{T_i}\sigma_\varepsilon^2$ (This is in a balanced sample, but not required)

From this estimator and the estimator of σ_ε^2 in step 1, we deduce an estimator of σ_u^2.

Step 3. The final step is a weighted instrumental variable estimator. The transformation of y_{it} and ($\mathbf{x_{1it}}$, $\mathbf{x_{2it}}$, $\mathbf{f_{1i}}$, $\mathbf{f_{2i}}$) is

$$v_{it}^* = v_{it} - (1-\theta_i)\bar{v}_i, where \theta_i = \sqrt{\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T_i\sigma_u^2}} \qquad \text{A-6}$$

where v_{it} denotes any of the aforementioned variables and $\bar{v}_i$ denotes a group mean. Note in the case of the time invariant regressors, the group mean is the original variable, and the transformation just multiples the variable by θ_i. The instrumental variables are $\mathbf{x}_{1it} - \bar{x}_{1i}$, $\mathbf{x}_{2it} - \bar{x}_{2i}$, $\mathbf{f}_{1i}$ and $\bar{x}_{1i}$. Note for the fourth set of instruments, the group mean is repeated for each member of the group.

APPENDIX B: SURVEYS AND INSTRUCTIONS

SURVEY [GROUP A]

Note: *Photos will be taken by using a digital camera, and after printing all of the photos, they will be deleted from the hardware, then the printed version will be given to subjects.*

Please rate each person in your group in terms of like and dislike, 1 being complete dislike and 5 being really like.

	1	2	3	4	5
	Completely Dislike	*Dislike*	*Indifferent*	*like*	*really like*
1. Name of the 1st member	☐	☐	☐	☐	☐

[picture of the 1st group member]

2. Name of the 2nd member	☐	☐	☐	☐	☐

[picture of the 2nd group member]

3. Name of the 3rd member	☐	☐	☐	☐	☐

[picture of the 3rd group member]

	1	2	3	4	5
	Completely Dislike	*Dislike*	*Indifferent*	*like*	*really like*

4. Name of the 4th member …….☐…….☐……….☐……….☐……..☐

 [picture of the 4th group member]

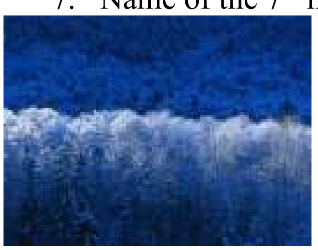
5. Name of the 5th member …….☐…….☐……….☐……….☐……..☐

 [picture of the 5th group member]

6. Name of the 6th member …….☐…….☐……….☐……….☐……..☐

 [picture of the 6th group member]

7. Name of the 7th member …….☐…….☐……….☐……….☐……..☐

 [picture of the 7th group member]

	1	2	3	4	5
	Completely Dislike	*Dislike*	*Indifferent*	*like*	*really like*
8. Name of the 8th member	☐	☐	☐	☐	☐

[picture of the 8th group member]

9. Name of the 9th member	☐	☐	☐	☐	☐

[picture of the 9th group member]

10. Name of the 10th member	☐	☐	☐	☐	☐

[picture of the 10th group member]

SURVEY [GROUP B]

Please rate each person in your group in terms of like and dislike, 1 being complete dislike and 5 being really like.

	1	2	3	4	5
	Completely Dislike	*Dislike*	*Indifferent*	*like*	*really like*
1. Name of the 1st member	☐	☐	☐	☐	☐
2. Name of the 2nd member	☐	☐	☐	☐	☐
3. Name of the 3rd member	☐	☐	☐	☐	☐
4. Name of the 4th member	☐	☐	☐	☐	☐
5. Name of the 5th member	☐	☐	☐	☐	☐
6. Name of the 6th member	☐	☐	☐	☐	☐
7. Name of the 7th member	☐	☐	☐	☐	☐
8. Name of the 8th member	☐	☐	☐	☐	☐
9. Name of the 9th member	☐	☐	☐	☐	☐
10. Name of the 10th member	☐	☐	☐	☐	☐

INSTRUCTIONS to SUBJECTS:

This is a two-part experiment. In this experiment, you will have a chance to earn a CONSIDERABLE AMOUNT OF MONEY BY FOLLOWING THE INSTRUCTIONS CAREFULLY. The money you earned will be paid in CASH at the end of the experiment.

Instructions for the first part: [For group A]

You are a GROUP "A" MEMBER. This is determined RANDOMLY.

In this part you will meet with your group members. You will have 15 minutes to share information about yourself regarding;

a- Name
b- Major
c- Hobbies and special interests
d- State and city you are from
e- Goals

It is extremely important NOT TO SHARE other information to insure the best results in this experiment and to maintain your privacy.

Then you will have 30 minutes to complete a puzzle that will be given to you as a group. If you are able to complete it ON TIME, as a group you will earn $100 and share it equally, which will give each of you $10. After the first part there will be a second part which will provide you with additional opportunities to earn more money.

<u>Instructions for the first part:</u> [For group B]

You are a GROUP "B" MEMBER. This is determined RANDOMLY.

In this part you will meet with your group members. You will spend a few minutes to share information about yourself regarding:

a- Name
b- Major
c- State and city you are from

It is extremely important NOT TO SHARE other information to insure the best results in this experiment and to maintain your privacy.

<u>Instructions for the second part:</u> [For group A & B]

In this part, we create a simulated market. There are 20 people in the market including your group members and Group B members. As a seller in this market, you have just one widget to sell. Each period, the price and the number of widgets that will be bought from the market will be shown to you on your screen.

For example, you will see

Market price: 130 experimental dollars

Market quantity: 7

This means if you want to sell your widget in this period, you can earn 130 experimental dollars every period for the rest of the experiment. Also, there will be only 7 people who will be able to sell their widgets.

Each period, after learning this information about the market price and quantity, you have to decide whether you want to re-enter the market or not. Names and groups of those who enter the market for that period will be seen by everybody on your screen.

You will have your group members' photographs with you through out the experiment, to help you remember each of your group members. But remember, there are also people who are not members of your group.

Then, you have to recommend to the buyer someone among those who enter the market. The buyer will buy widgets from those who get recommended more than the rest of the sellers. In this part, you can recommend anyone but NOT YOURSELF even if you are in the market.

Based on the recommendations, those who are recommended more than others will sell their widget. The ranking will be done by using the number of recommendations and those who rank the highest will sell their widgets depending on the need of the market. For example, if market quantity is 7, and you ranked 6^{th} then you will sell your widget in this period and an automatic contract will be formed. If market quantity is 5 then with this ranking you will not be able to sell the widget. In case of a tie, the computer will choose the seller RANDOMLY. As you see your earnings will depend on the recommendations you get from other people in the market.

After you sell your widget, an automatic contract is formed between you and the buyer for the rest of the periods. Meaning, you will earn the same amount of money as if you sold your widget at every period. Even if you have a contract, you can still re-enter the market. To re-enter the market it will cost you (20 %) of your period earnings. For example, you had a contract at 130 experimental dollars, and now the market price is 180 experimental dollars. Then if you want to enter the market you are required to give up 20 % of your 130 earnings which is 26 experimental dollars.

The experiment is a 20-period experiment. Every period, the same procedure is followed.

TABLE A-1 Data Statistics for Each Treatment

	Highest earnings A	Lowest earnings A	Highest earnings B
COST1-NE	32.84	16	32.4
COST2-NE	30	12.28	32.4
COST3-NE	32.6	13.2	32.4
COST4-NE	32.84	13.52	32.3
COST5-NE	32.4	10.8	32.4
COST6-NE	32.84	13.97	32.4
COST1-E	32.88	19.64	32.4
COST2-E	35.16	17.4	32.84
COST3-E	35.54	13.65	32.3
COST4-E	32.4	17.19	30
COST5-E	32.4	0	32.4
COST6-E	32.56	14.23	30

	Lowest earnings B	Average earnings A	Average earnings B
COST1-NE	15.4	23.739	23.397
COST2-NE	16.5	20.4	23.11
COST3-NE	13.05	21.287	20.308
COST4-NE	6.6	22.01	17.21
COST5-NE	11.5	18.862	22.497
COST6-NE	14	22.561	19.774
COST1-E	18.86	27.02	26.17
COST2-E	19.2	23.31	24.18
COST3-E	16.5	22.84	21.62
COST4-E	15.85	25.22	20.54
COST5-E	16.28	17.748	23.018
COST6-E	8.21	20.771	18.534

TABLE A-2 Data Collected in Experiments

	Group A	Group B	ratings	rata	ratb	gra	grb
e1	19.47	22.88	4.111111	0	0		
e1	32.4	23.76	4.444444	0	1		23.76
e1	29.7	29.1	4.444444	1	1	29.7	29.1
e1	27.16	22.46	4.444444	1	1	27.16	22.46
e1	32.88	32.4	4.666667	1	1	32.88	32.4
e1	32.6	23.74	4.666667	1	1	32.6	23.74
e1	25.66	32.4	4.222222	1	1	25.66	32.4
e1	23.72	30	4.222222	0	1		30
e1	19.64	18.86	4.111111	0	1		18.86
e2	23.64	19.2	4.285714	1	1	23.64	19.2
e2	23.66	30.2	4.285714	1	1	23.66	30.2
e2	19.57	23.36	4.285714	0	0		
e2	17.4	32.84	4.285714	1	1	17.4	32.84
e2	19.44	21.84	4	1	1	19.44	21.84
e2	35.16	20.08	4.428571	1	1	35.16	20.08
e2	24.32	21.78	4.285714	1	1	24.32	21.78
e3	23.52	18.12	4.125	0	1		18.12
e3	21.76	20.76	3.625	1	1	21.76	20.76
e3	24.56	23.32	3.875	1	0	24.56	
e3	19.2	27.48	4	1	1	19.2	27.48
e3	13.65	17.06	4.125	0	1		17.06
e3	35.54	32.3	4.125	1	1	35.54	32.3
e3	16.28	16.5	4	1	1	16.28	16.5
e3	28.25	17.45	4.375	0	1		17.45
e4	25.44	17.3	4.111111	1	1	25.44	17.3
e4	28.98	19.88	4.444444	1	1	28.98	19.88
e4	17.19	15.85	4	0	1		15.85
e4	32.4	18.33	3.333333	1	1	32.4	18.33
e4	32.4	19.2	4.111111	1	1	32.4	19.2
e4	25.2	16.77	4.333333	1	0	25.2	
e4	22.29	30	4	1	1	22.29	30

e4	19.36	30	3.555556	1	1	19.36	30
e4	23.76	17.6	4.222222	1	1	23.76	17.6
e5	0	16.28	3.6	0	1		16.28
e5	11.75	32.4	3.7	1	1	11.75	32.4
e5	32.4	18.68	4	1	0	32.4	
e5	30.24	21.78	3.8	1	0	30.24	
e5	24.7	20.08	4.1	1	1	24.7	20.08
e5	16.7	30.6	3.5	1	1	16.7	30.6
e5	18.72	18.12	3.9	0	0		
e5	4.94	25.2	3.9	0	1		25.2
e5	18.96	22.16	3.7	0	1		22.16
e5	19.07	24.88	3.7	1	1	19.07	24.88
e6	14.88	21.56	4.3	0	1		21.56
e6	23.36	21.05	4.3	1	1	23.36	21.05
e6	30	14.25	4.7	1	0	30	
e6	18.85	8.21	4.1	0	0		
e6	15.38	30	4.3	0	1		30
e6	22.11	13.81	4.5	1	1	22.11	13.81
e6	14.23	22.08	4.2	0	1		22.08
e6	18	13.66	4.3	1	0	18	
e6	18.34	17.36	4.3	0	1		17.36
e6	32.56	23.36	4.4	1	1	32.56	23.36

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