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EARNINGS OF SELF-EMPLOYED WORKERS AND PEER EFFECTS AMONG TEENAGERS

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ABSTRACT

EARNINGS OF SELF-EMPLOYED WORKERS AND PEER EFFECTS AMONG TEENAGERS

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This dissertation contains three essays in applied microeconomics.

Chapter 1 revisits the empirical results of Lazear and Moore [Edward Lazear and John Moore (1984) "Incentive, Productivity, and Contract" *Quarterly Journal of Economics* 99]. That paper found that empirical experience-earnings profiles were flatter for self-employed workers and argued that this supported the Lazear contract theory that claim firms use life-cycle backloaded payment systems to work around principal-agent problems between firms and workers. This chapter reproduces the Lazear and Moore result on more modern data, but argues for an alternative interpretation. In particular, this chapter argues that self-employed workers face more wage variation but enjoy a higher return for human capital. A model based on these assumptions can produce flatter experience-earnings profile since self-employed workers start their career with more human capital and due to opportunity cost, they invest less in human capital on the job. The chapter develops implications of the model not found in the Lazear contract model and concludes by developing support for these implications.

Chapter 2 attempts to explain the lower earnings among self-employed workers found by Hamilton [Barton Hamilton (2000) "Does entrepreneurship pay? An Empirical Analysis of the Return of Self-Employment" *Journal of Political Economy* 108]. That paper found 20% lower earnings of self-employed workers with 10 years of business tenure than comparable salaried workers with 10 years of job tenure. This difference in earnings can in principal be explained by the compensating wage differential theory when self-employed jobs have attractive non-monetary aspects. Using the National Longitudinal Survey Youth 79 (NLSY79), this chapter tests whether self-employment is as-

sociated with higher global job satisfaction. By looking at changes in job satisfaction for individuals over time, I overcome the difficulty of interpreting differences in subjective job satisfaction scores across individuals that cross-sectional analysis would require. Using my estimates, I calculate the monetary value of the non-monetary aspects of self-employment and find that one dollar earned while a self-employed worker is equivalent to as much as three to four dollars earned as a salary or wage worker. Although the valuation is surprisingly high but the the direction of the estimate is consistent with the compensating wage differential hypothesis. Although job satisfaction is a partial component of workers' total utility, the value of self-employment in terms of job satisfaction is sufficiently high to support the compensating differential hypothesis as an explanation for lower earnings among self-employed workers. I also evaluate several other explanations for the surprisingly high valuation of self-employment.

Chapter 3 attempts to estimate peer effects on substance usage among teenagers. This chapter first summarizes the problems in the identification of peer effects. The existence of unobserved characteristics of individuals and endogenous sorting into reference groups based on unobserved characteristics causes problems in the identification of peer effects. The solutions for this problem are: 1. To control "unobservable" through including plenty of explanatory variables using rich data set or using sibling method to difference out unobservable. 2. To use natural experimental situation in which reference group is assigned randomly. 3. To use economic theory to get a prediction that arises only from peer effect but not from contextual or correlated effect. In this chapter, the method 1 was taken. Significant peer effects were found on substance usage among teenagers.

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Chapter 1

Human capital accumulation of salaried and self-employed workers

1.1 Introduction

Worker's wage growth with work experience is one of the most robust empirical findings in economics. Lazear (1979) explained wage growth among salary/wage workers based on principal-agent theory. In this model, workers' behavior is not perfectly observed and workers' shirking is detected only by chance. According to Lazear, it is optimal for an employer to pay his employee less than the worker's marginal product when the worker is young and more than the worker's marginal product when the worker is old. This payment system discourages workers from shirking: The worker is fired when the shirking is detected and thus cannot receive his money back.

Human capital theory also predicts wage growth with work experience because of worker's skill formation. Since Lazear's theory and human capital theory are not mutually exclusive, it is very difficult to attribute the observed wage growth exclusively to either model.

As an indirect test of Lazear's theory, Lazear and Moore (1984) (LM hereafter) compared the wage growth of salary/wage workers and self-employed workers. Since self-employed workers do not have an incentive to shirk, the wage growth of self-employed workers can be attributed to the human capital accumulation. Assuming identical human capital accumulation between salary/wage (SW) workers and self-employed (SE) workers, the difference of wage growth between SW workers and SE workers can be attributed to Lazear's theory. In fact, LM found a steeper wage-experience profile among SW workers than SE workers and used the finding as evidence to support Lazear's theory.[1]

There are several other theories that explain wage growth on the job. Salop and Salop (1976) proposed the model in which firms offer upward tilted wage profiles to screen desirable workers for firms. In their model, workers have heterogeneous probability to quit their job and this is private information of workers. It is costly for firms that workers quit because of necessary training for new workers. In this situation, firms use tilted up wage profile as a screening device so that only workers with low probability to quit apply for the job. According to their theory, self-employed workers have flatter wage profile than those of salary/wage workers since self-employed workers do not have to utilize tilted up wage profile as a screening device. It is important to emphasize that Salop and Salop's theory and Lazear's theory render the same prediction about the difference between salary/wage and self-employed workers and, accordingly, we cannot distinguish those two theories only looking at wage profiles of both jobs.

Jovanovic (1979) attempted to explain upward sloping wage profile among workers using the concept of matching quality. In his theory, workers gradually learn the quality of job match that is specific to a worker and a job, and workers who realize bad match quit their job. As a result of this self-selection, wage rises among job stayers. Workers learn the quality of job match only gradually because they cannot distinguish wage shock due to job match and idiosyncratic shock at each moment. Using series of wage realization, workers infer their job match quality. In this setting, average wage growth

[1] LM in fact estimated wage equation for each occupation and found positive correlation between the present value of life time earnings and the slope of wage-experience profile among salary or wage workers but not among self-employed workers. They interpreted this as evidence of productivity enhancing effects of deferred payment system among salaried workers. However, the life time income was calculated based on the estimated coefficients of the wage equation that includes experience term, so when slope coefficient is nearly zero, which were the case for self-employed workers in many occupations in their study, then the life time income is determined irrelevant of slope coefficient. Thus, the difference of wage-experience profile is crucial to derive their results.

among job stayers depend how fast the workers who realizes bad job match change their job. As several studies indirectly show, self-employed workers tend to invest in their own business at the start up.[2] If this investment is sunk, then self-employed workers who realize bad job match are less likely to change the job due to the income flow generated from the sunk investment. In this sense, self-employed workers are "foot fixed" workers while salary/wage workers are "foot lose" workers. Thus Jovanovic's theory also potentially explains Lazear and Moore's finding.

These discussions show the possibility that Lazear's. Salop and Salop's and Jovanovic's theory can potentially explain the observed flatter earnings profiles of self-employed workers than salary/wage workers. Among the alternative explanations for LM's findings, the human capital theory is exclusively pursued in this paper since this theory does not require any type of informational imperfection. It would be most striking to obtain the theoretical prediction consistent with LM's finding assuming perfect information. Accordingly, the purpose of this paper is to propose a model that predicts the flatter earnings-tenure profile among SE workers based only on human capital theory.

To develop this model, two crucial aspects of self-employment that differentiate self-employment from salary/wage job are considered; firstly, the larger variation in income compared with that experienced by SW workers, secondly, the higher return for human capital than that of SW workers. Modelling these two characteristics of SE's wage determination with workers' risk aversion, workers' optimal human capital investment decision produces a steeper wage profile among SW workers, as LM observed. In this model, the workers choose to be SW or SE workers in the first period. Since to be SE is risky, the worker with high human capital selects SE because the higher return for human capital compensates for the risk. Under the convexity assumption of human capital production, workers with higher human capital invest less in their human capital on the job due to higher opportunity cost. Thus SE workers, who have higher human

[2] See Dunn and Holtz-Eakin (2000) for example.

capital as a result of self-selection, tend to have a flatter wage profile compared with SW workers because of less human capital investment on the job.

The structure of the rest of this paper is as follows. The second section examines the wage risk for self-employed workers since the wage risk of self- employment is a crucial assumption for the main conclusion. The third section introduces the model of human capital accumulation under the income risk. The fourth section provides evidence consistent with the model. The fifth section concludes.

1.2 Replication of Lazear and Moore (1984)'s results and the wage risk of self- employed workers

1.2.1 The model and estimation

In this section, I replicate the results obtained in LM using a different data set and test whether the wages of SE workers are more volatile than those of SW workers.

Data for the years 1985 through 1998 were taken from NLSY79. The sample is restricted to white males and is used to estimate the model:

$$\ln w_{it} = X_{it}\beta_1 + \beta_2 s_{it} + s_{it}(X_{it} - \bar{X})\beta_3 + c_i + u_{it}, \tag{1.1}$$

where w_{it} is hourly wage rate[3] and X_{it} is a vector of standard control variables in Mincer type wage equation and $\bar{X}$ is a vector of sample mean of each explanatory variable,[4] s_{it}

[3]Hourly rate of pay is constructed by the Center for Human Resource Research (CHRR) based on respondents' usual earnings (inclusive of tips, overtime, and bonuses but before deductions) per hour, day, week or month. Then this earnings is divided by the hours worked in the corresponding time unit. Hours worked might be seriously measured with error among SE workers. Then the wage rate among SE workers may be subject to larger measurement error. However, the analysis in the next section shows that measurement error that is correlated with SE status does not affect the conclusion in this section. CHRR requests wages/salaries/tips income and business/firm income along with other income categories from both wage/salary workers and self-employed workers. Thus there is less concern that self-employed workers earnings contains capital income, in addition to labor income, which is the main concern for the measurement of income among self-employed when CPS is used. Therefore the measurement of earnings for self-employed workers in NLSY 79 is as good as those in SIPP that were used in Hamilton (2000). Although Hamilton (2000) also used the earnings that include capital gain as an alternative earnings measure of self-employed workers, I just focus on the labor earnings of self-employed worker here.

[4]The variables included in the regression appear in Table 1-1. The variable names are self-explanatory.

is a dummy variable that takes one if the worker is self-employed and c_i is individual heterogeneity. The interaction with the self-employed dummy is included to replicate LM's findings. The model is estimated by both pooled OLS and fixed effects assuming $E[u_{it}|X_i, s_i, c_i] = 0$, where $X_i = [X_{i1}, ..., X_{iT}]$. The estimation results appear in the first and second column of Table 1-1. The return to experience among SE workers (about 7% for the first year) is almost 60% of SW workers' (about 11% for the first year). In addition, there is almost no return to tenure among SE workers, while SW workers enjoy a return of 3.2% for the first year of tenure. The difference of hourly wage between SW workers and SE workers are evaluated at various points of experience and tenure. Although SE workers enjoy SE premium when they start off their business, but this SE premium declines due to lower return to experience and tenure. The lower return to tenure among SE might be because of the Lazear contract or less on-the-job human capital investment by SE workers, but lower return to general work experience among SE worker can be explained by less human capital investment among SE workers but not by the Lazear theory since it only explains the higher return to *tenure* among SW workers due to implicit incentive contract. Similarly, Salop and Salop's theory cannot explain lower return to experience among self-employed workers since the theory only explains the return to tenure. Moreover, even if self-employed workers are "locked" in their jobs due to the investment made at their business start up, Jovanovic's theory explains lower return to business tenure but does not explain lower return to experience among self-employed workers. These results were not found in LM since they only used potential experience as an explanatory variable but did not use tenure because of data limitation. In sum, SE workers earn higher wages and experience less wage growth.

Using the residual of the previous *fixed effects* estimation as the dependent variable,

$$\hat{u}_{it}^2 = \gamma_0 + \gamma_1 s_{it} + a_i + v_{it}, \tag{1.2}$$

is estimated.[5] Since we are interested in the wage variation faced by an individual, I

[5]Essentially this is Breush-Pagan's test for heteroscedasticity.

used residuals from *fixed effects* wage regression to create a measure of wage variation. The model (1.2) is estimated by both OLS and fixed effects considering the possibility that workers with high volatility due to intrinsic reason self-selects into SE. We are interested in if $\gamma_1 = 0$. The results of the OLS and fixed effects estimation appear in Table 1-1, Column (3) and (4). By using the results of the OLS regression, we can say that the conditional wage variance among SE workers is about 2.6 times larger than that of the salaried workers. Also, the results are essentially the same for both OLS and fixed-effects. From this evidence, we conclude that being self-employed is riskier than being a SW worker.

1.2.2 The issues of measurement error

There is a possible flaw in the previous analysis due to measurement error in the wages of self-employed workers. Smaller return to experience and tenure among SE workers may be due to measurement error in the wages of SE that are systematically correlated with experience or tenure. It is also likely that larger conditional variance of wages among SE workers is due to measurement error. Joulfaian and Rider (1998) report that SE workers underreport their income by 18% on average, using the Tax Payer Compliance Measurement Program data collected by the IRS. Although respondents have no incentive to avoid taxation by underreporting their income in the case of NLSY, underreporting is still possible because respondents may refer to their tax forms to report their income.[6] The following analysis explicitly discuss the issue of measurement error. The model with measurement error is following:

$$\ln w^*_{it} = X_{it}\beta_1 + \beta_2 s_{it} + s_{it}(X_{it} - \bar{X})\beta_3 + c_i + e_{it}, \tag{1.3}$$

$$\ln w_{it} = \ln w^*_{it} + d_i + b_i s_{it} + u_{it}, \tag{1.4}$$

[6] In addition to the measurement error due to under reporting, measurement error of hourly rate of pay can be introduced through the division of (daily, weekly or monthly) earnings by hours worked in corresponding period. Since hours of work may be more erroneous among SE workers, the measurement error in hourly rate of pay can be correlated with SE dummy. However, argument in this section carries over if the individual tendency to mis-report hours worked is constant while a worker is in the same type of job.

where d_i is an individual specific tendency to misreport regardless of employment status and b_i is an individual specific tendency to misreport wages when the respondent is self-employed. The assumption that these individual tendencies are time-invariant is crucial in the following discussion. These tendencies (b_i, d_i) and errors in equations (e_{it}, u_{it}) are assumed to be independent. The assumptions on error terms, $E[e_{it}|b_i, c_i, d_i, X_i, s_i] = 0$, $E[u_{it}|b_i, c_i, d_i, X_i, s_i] = 0$ and $E[e_{it}^2|b_i, c_i, d_i, X_i, s_i] = (1 + \phi s_{it})\sigma_e^2$ are assumed. To test if self-employed workers face the larger risk, we are interested in if $\phi = 0$. The model that is actually estimated is

$$\ln w_{it} = X_{it}\beta_1 + \beta_2 s_{it} + s_{it}(X_{it} - \bar{X})\beta_3 + c_i + e_{it} + d_i + b_i s_{it} + u_{it}. \quad (1.5)$$

Applying the fixed effects transformation, we obtain

$$\ln w_{it} - \overline{\ln w_i} = (X_{it} - \bar{X}_i)\beta_1 + \beta_2(s_{it} - \bar{s}_i) + (s_{it}X_{it} - \overline{s_i X_i})\beta_3 + e_{it} + b_i(s_{it} - \bar{s}_i) + u_{it} \quad (1.6)$$

In this situation, the fixed effects estimator is not a consistent estimator since plim $\hat{\beta}_2 = \beta_2 + b$, where $b = E(b_i)$. Thus the fixed effects estimator of β_2 estimates the lower bound of β_2 given $b < 0$.

Another possible measurement error arises from the differential concept on the income between SW workers and SE workers. SE workers may report return for physical capital of their own business as their wages: they also may subtract the cost of physical investment in their own business from their wages. It is likely that SE workers invest in physical capital when they start their businesses and collect the return later. Then the wages of short tenured SE workers are understated and the wages of long tenured SE workers are overstated. Due to this measurement error, the return to tenure among SE workers may be overestimated. Regardless of this possibility of upward bias, the estimated return to tenure among SE workers are almost zero.

The conditional variance of measurement error may also depend on self-employment status through the effect of b_i. Define the error term in (1.6) as $h_{it} = e_{it} + u_{it} + b_i(s_{it} - \bar{s}_i)$. Then

$$E[h_{it}^2|X_i, s_i] = (1 + \phi s_{it})\sigma_e^2 + \sigma_u^2 + (s_{it} - \bar{s}_i)^2 E[b_i^2|X_i, s_i]. \quad (1.7)$$

The last term tells us that the job status changer tends to have a larger variance. Assuming $E[b_i^2|X_i, s_i] = \sigma_b^2$, regressing the residual of fixed effects wage equation on s_{it} and $(s_{it} - \bar{s}_i)^2$ renders consistent estimators of ϕ and σ_b^2. The OLS and fixed effects estimates appear in column (5) and (6) of Table 1-1. Although the estimate of φ diminishes slightly, it is still large and statistically significant. Therefore, we still conclude that being a self-employed worker is riskier than being a wage-salary worker.

1.3 The model

Let us suppose that each worker lives for two periods and that each worker is endowed with one unit of time for each period. Each worker knows his ability in the first period. Each worker has the following preference with constant absolute risk aversion:

$$\hat{U}_i = -\exp[-\gamma_i(w_{i1} + w_{i2})] \tag{1.8}$$

where γ_i is the degree of absolute risk aversion of worker i and w_{it} is the wage offer for worker i at time t. The wage offer depends on job choice, meaning whether the worker is self-employed or salaried worker. The wage offer for job j is

$$w_{itj} = b_j(1 - n_{it})h_{it} + e_{itj},\ e_{itj} \sim N(0, \sigma_j^2) \text{ for } j = SE, SW, \tag{1.9}$$

where h_{it} is the human capital of worker i at period t, $n_{it} \in [0, 1]$ is the portion of time devoted to the human capital accumulation by the worker i at time t. The initial human capital h_{i1} is given as an endowment for each worker and includes human capital accumulated through education and innate ability.[7] The human capital for both periods is assumed to be general across the jobs. The parameter b_j, which is exogenously given by the labor market for the workers, is the unit price of human capital in job j. The random variable e_{itj} is a shock to the wage. This model assumes e_{itj} is independently distributed across individual, time, and two jobs. Taking expectation of the life-time

[7] While recognizing the endogeneity of the educational decision, I have treated this as given since the main interest of this analysis is on-the-job human capital accumulation.

utility and using the ordinal property of utility function,

$$EU = b_j(1 - n_{i1})h_{i1} - (\gamma_i/2)\sigma_j^2 + b_j(1 - n_{i2})h_{i2} - (\gamma_i/2)\sigma_j^2 \tag{1.10}$$

is obtained.[8] Each worker has access to the following human capital accumulation technology:

$$h_{i2} = h_{i1} + \delta(n_{i1}h_{i1})^{\alpha}, \alpha \in (0, 1), \tag{1.11}$$

where δ is efficiency of human capital investment on human capital accumulation.[9] The parameter α represents a worker's learning ability, which is assumed to be identical for all workers. This technology shows that the worker with higher human capital is more productive in the production of additional human capital, but the effect diminishes, since $\alpha \in (0, 1)$.

Two assumptions are made that distinguish SW and SE workers.

Assumption 1 $\sigma_{SE}^2 > \sigma_{SW}^2$, i.e., the wages of SE workers are more volatile than those of SW workers. The empirical evidence supports this assumption as seen in the previous section.

Assumption 2 $b_{SE} > b_{SW}$, i.e., the return for human capital is higher for self-employed workers. This assumption is justified by the higher returns to education among SE workers than SW workers in previous study that utilize Census data.[10] For example, Fairlie and Meyer (1996) found 0.90 as the return to education among SE workers while they found 0.59 among SW workers. The data used in this study does not indicate higher return to education, though.

Under these assumptions, each worker maximizes his lifetime expected utility (1.10) by choosing n_{i1} and a career path ($\{j\}_{t=1}^2$) under the constraint of human capital accu-

[8]See Appendix for derivation.

[9]This functional form of human capital accumulation is standard in the literature. See Heckman (1976).

[10]See Borjas and Bronars (1989) and Fairlie and Meyer (1996). In particular Fairlie and Meyer (1996) used 1990 Census Public Use Microdata 5-percent sample that contains 14881 SE sample and 100514 SW sample.

mulation technology (1.11).[11] Since indirect utility from the career path of SE-SW is always dominated by the indirect utility from other career pathes, we should consider three possible career paths of SE - SE, SW - SW, and SW - SE.

The optimal human capital investment time, n_{i1}, is

$$n_{i1} = \begin{cases} (\delta\alpha)^{\frac{1}{1-\alpha}} h_{i1}^{-1}, & \text{for job stayers.} \\ (\frac{b_{SE}}{b_{SW}})^{\frac{1}{1-\alpha}} (\delta\alpha)^{\frac{1}{1-\alpha}} h_{i1}^{-1}, & \text{for job changers.} \end{cases} \tag{1.12}$$

These solutions show the human capital investment time decreases in the level of initial human capital.[12]

By substituting the optimal n_{i1} in the objective function of each career path, we obtain the following indirect utility functions for each career path for each individual i.

$$v_{j-j}(h_{i1}, \gamma_i) = 2b_j h_{i1} - \gamma_i \sigma_j^2 + b_j \delta^{\frac{1}{1-\alpha}} (\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}}) \text{ for } j = SE, SW, \tag{1.13}$$

$$\begin{aligned} v_{SW-SE}(h_{i1}, \gamma_i) &= (b_{SW} + b_{SE})h_{i1} - (\gamma_i/2)(\sigma_{SW}^2 + \sigma_{SE}^2) \\ &\quad + b_{SW}^{\frac{-\alpha}{1-\alpha}} b_{SE}^{\frac{1}{1-\alpha}} \delta^{\frac{1}{1-\alpha}} (\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}}) \end{aligned} \tag{1.14}$$

These expressions tell us that the choice of career path depends on each worker's level of initial human capital and the degree of risk aversion. The relationship between lifetime utility for each career path and initial human capital is graphed in Figure 1-1 given the degree of risk aversion. This graph shows the lifetime utility of being a SE worker is higher than being a SW worker for the high human capital worker. In addition, the graph shows that the worker with a "medium" level of human capital switches jobs in the middle of his career.

The worker with higher initial human capital selects self-employment. This selection affect the wage growth of SE and SW workers. The "average" wage growth for each

[11] As a result of optimization, $n_{i2} = 0$ is trivially chosen.

[12] There are two factors related to the initial human capital level and human capital investment. First, from (1.11) the worker with higher human capital is more productive in human capital accumulation. However, this effect is diminishing because the term $(n_{i1}h_{i1})$ is exponentiated by $\alpha \in (0,1)$. Second, the worker with higher human capital pays more opportunity costs of human capital investment, which is $b_j n_{i1} h_{i1}$. The marginal benefit of investment diminishes in h_{i1} but the marginal cost is constant in h_{i1}: thus the worker with high h_{i1} chooses lower n_{i1}. The convexity of human capital production function is the crucial assumption to derive this result.

career path is,[13]

$$g_{j-j} = \frac{Ew_{2j}}{Ew_{1j}} = \frac{h_{i1} + \delta^{1/(1-\alpha)}\alpha^{\alpha/(1-\alpha)}}{h_{i1} - \delta^{1/(1-\alpha)}\alpha^{1/(1-\alpha)}} \text{ for } j = SE, SW, \tag{1.15}$$

$$g_{SW-SE} = \frac{Ew_{2SE}}{Ew_{1SW}} = \frac{b_{SE}}{b_{SW}} \frac{h_{i1} + \delta^{1/(1-\alpha)}((b_{SE}/b_{SW})\alpha)^{\alpha/(1-\alpha)}}{h_{i1} - \delta^{1/(1-\alpha)}((b_{SE}/b_{SW})\alpha)^{1/(1-\alpha)}}. \tag{1.16}$$

If the initial level of human capital is given, the wage profiles of the SE and the SW workers are identical and it decreases as h_{i1} increases and converges to one. However, what we observe is $g_{SE-SE} < g_{SW-SW}$ because the SE worker's h_{i1} is higher than the SW worker's. Thus the observed difference between wage profiles is the result of the workers' heterogeneity in the initial level of human capital.

1.4 Supporting evidence of the model

1.4.1 SE workers have higher human capital

The theory discussed in the previous section predicts that the worker with higher human capital selects self-employment. With respect to the observable characteristics, several studies report that the worker with high education is more likely to be self-employed.[14]

It is a stylized fact that the worker who has a self-employed father is more likely to be a SE worker, even after controlling for inheritance.[15] In particular, Dunn and Holtz-Eakin (2000) emphasize the importance of the intergenerational transmission of human capital rather than the mitigated liquidity constraint to explain this finding, since they found a very large effect of the parent's self-employment status on the son's selection into self-employment even after controlling the amount of the parents' assets. They also found that the son of a successful self-employed worker is likely to be self-employed. From this finding, they conclude that the transmission of human capital is the important channel to explain the intergenerational correlation of self-employment status. Although

[13]Although the expected value of a ratio is not a ratio of expected values, this measure gives us a rough idea.

[14]See Borjas and Bronars (1989) and Evans and Leighton (1989)

[15]See Lindh and Ohlsson (1996) Blanchflower and Oswald (1998), Hout and Rosen (1999) and Dunn and Holtz-Eakin (2000). By controlling inheritance, the researchers try to partial out the effect of liquidity constraint.

their findings may imply the transmission of human capital that is specific to the SE, the theoretical discussion made in this paper still holds since the worker with "any kind of" higher human capital experiences lower wage growth. These results support the prediction of the model presented here: Self-employed workers experience lower wage growth because of higher level of initial human capital.

1.4.2 Less human capital accumulation among SE workers

The model predicts less human capital accumulation among SE workers. This prediction can be directly tested through the comparison of recorded human capital investment behavior by SE and SW workers. School attendance or participation to training while working are good measure of human capital investment. The NLSY79 records the participation to training in a consistent way after 1988 survey, thus analysis sample in this subsection is restricted after 1988. This sample restriction reduced the sample size to 17825 for school enrollment analysis and 17818 for training participation analysis. This restriction also largely excludes college students who have part-time job since respondents are at least age 24 in 1988.

Firstly, school enrollment while working is analyzed. Table 1-2 tabulates any school enrollment since last interview by the types of job. While 9 percent of SW workers enrolled in school between last and current interview, only less than 6 percent of SE workers enrolled. To control the difference in the characteristics of SW and SE workers, school enrollment was regressed on self-employment dummy as well as observed characteristics by OLS. Fixed effects linear probability model was also estimated to deal with individual heterogeneity. Both OLS and FE results, which appear in Table 1-3, indicate that SE workers are about 2 percentage points less likely to enroll in school while average enrollment rate is about 8.7 percent.

Secondly, participation to training is analyzed. The participation to training is not straightforwardly comparable between SE and SW workers since some training that takes place in SE sector may not be recognized just because it does not take the form of formal training. To work around this problem, Table 1-4 Panel A breaks the participation to training into types of training that workers participate. On-the-Job-Training ("Apprenticeship Program," "Formal Company Training Run by Employer or Military Training" or "Seminars or Training Programs at Work Not Run by Employer") may not be comparable between SE and SW workers since those training programs are less likely to exist in SE sector in formal fashion and consequently actual participation to comparable informal programs by SE workers may be misclassified as non participation. On the other hand, the participation to Off-the-Job Training ("Business School," "Vocational or Technical Institute," "Correspondence Course," "Seminars or Training Programs outside of Work" and "Vocational Rehabilitation Center") is comparable between SE and SW workers since the definition of these training programs are presumably identical across SE and SW workers. Table 1-4 Panel A shows that 18.91 percent of SW workers participate in training while 9.21 percent of SE workers participate in training. Restricting our interest to Off-the-Job Training (Off-JT hereafter) renders the same picture, although the difference is largely reduced. While 6.20 percent of SW workers participate in Off-JT, 5.00 percent of SE workers participate in Off-JT. To control the difference in observed characteristics between SE and SW workers, liner probability models with and without fixed effects are estimated. The OLS result that appears in Column (1) of Table 1-5 indicates that SE workers are 9.7 percent points less likely to participate in training, while FE result that appears in Column (2) of Table 1-5 indicates that SE workers are 5.0 percent points less likely to participate in training. As for Off-JT, OLS result that appears in Column (3) of Table 1-5 indicates that SE workers are 1.2 percent points less likely to participate in Off-JT while FE result (Column (4) of Table 1-5) indicates 1.0 percent points reduction. All of the results above indicate that SE workers are less likely to participate in training and accordingly invest less in their human capital on the job.

The model also predicts that SW workers who become SE in the second period invest more in their general human capital in the first period because of lower opportunity cost of human capital investment and higher return to human capital. To test this theoretical prediction, using SW workers as sample, the participation to training is regressed on future SE dummy and other controls by OLS.[16] The result of estimation appears in Column (5) in Table 1-5 but this result indicates that future SE workers are less likely to participate in training in general. This result does not necessarily contradict with the theory since SW workers who become SE in the future may invest less in firm specific human capital. Thus it is important to disentangle investment in general human capital from investment in firm specific human capital. Ideally, general human capital investment should be regressed on future SE dummy and other controls. As an attempt to implement this idea, the participation to Off-JT or training whose cost is paid by workers or government are regressed on future SE dummy and controls. In particular, the information who beard the cost of training is important since Becker's traditional theory predicts that training that endows workers with general human capital is paid by workers while the cost of investment in firm specific human capital is shared by both workers and firms. Although training whose direct cost is paid by employer might be eventually paid by workers through lower wage, training whose direct cost is paid by employee or government bounds the minimal set of training that presumably endows workers with general human capital. The results of regressions of Off-JT and own/goverment paid training participation on future SE dummy and other variables appear in Column (6) and (7) of Table 1-5. The participation to Off-JT does not differ practically among SW workers who stay in firm and who become SE in the future. However, future SE workers are 1.4 percent more likely to participate in the training whose cost is paid by his/her own or government. Considering only 3.3 percent of SW workers participate in own/government paid training, the difference is large. This result imply that prospective SE workers invests more in general (portable) human capital while they are SW workers.

[16] Future SE dummy varies within individual for those who switch to SE and switch back to SW but no prospect to be SE again. Since identification based on those observations are weak, fixed effects estimation is not implemented.

1.4.3 Both winner and loser select SE?

The model predicts a very simple selection rule: The worker with high human capital selects SE. A sensible criticism for this prediction is that there are two kinds of SE workers. The first kind is an eligible entrepreneur and the second kind is the SE worker who is not qualified to work for a firm and is forced to work by himself. If this story describes the real world. it is not surprising that the latter group experiences less wage growth since the less eligible worker has less learning ability and experiences less wage growth.

To examine this possibility. I studied the distribution of ability among self-employed and wage-salary workers. If there is a "two tail selection rule" among SE workers, we should find bimodal distribution of ability among SE workers that have two peaks at high and low ability. As a proxy for the ability I used the AFQT89 (Armed Force Qualifying Test) score that is contained in NLSY 79. The result of the kernel density estimation of the distribution of test scores for the SE and SW workers appears in Figure 1-2. Comparing the two distributions. we find bimodal distributions among SW workers and SE workers. However SW workers have peaks on high sores and low scores but SE workers have perks on high scores and medium scores . This evidence shows that "two tail selection rule" is more likely among SW workers than among SE workers.

1.5 Conclusion

In this paper. the human capital accumulation by self-employed (SE) and salaried and wage (SW) workers was analyzed. Under the assumptions that the wages of SE workers are more volatile than salaried workers' and the wages of SE workers more sharply reflect their human capital. SE workers invest less in their human capital because of their higher initial human capital. This difference in human capital investment behavior results in a flatter wage profile for SE than SW workers. This theory was indirectly supported by the empirical facts about self-employed workers. In particular. the empirical evidence shows that the SW workers with future SE prospect accumulate more general human capital on the job and this evidence is consistent with the model developed in this paper.

The model shows that the self-employed workers are not necessarily a good "control" group to test the Lazear contract, since not only does the incentive effect of the Lazear contract produce the steeper wage profile of salaried workers, but the difference in human capital investment has this effect as well. This conclusion does not deny the existence of the Lazear contract, nor the results produced by Lazear and Moore (1984). However, simply attributing the difference of wage profiles to the incentive effect of the Lazear contract may overestimate its importance.

The full-blown test of the theory introduced in this paper is left for future research.

Appendix

The derivation of (1.10) is as follows:

$$
\begin{aligned}
E\hat{U}_{it} &= \int\int -\exp[-\gamma_i(w_{i1} + w_{i2})]dF(e_{i1j})dG(e_{i2j}) \\
&= -\int \exp[\gamma_i(b_j h_{i1}(1 - n_{i1}) + e_{ij1})]dF(e_{ij1}) \\
&\quad \cdot \int \exp[\gamma_i(b_j h_{i2}(1 - n_{i2}) + e_{ij2})]dG(e_{ij2}) \\
&= -\exp[-\gamma_i(b_j(1 - n_{i1})h_{i1} - (\gamma_i/2)\sigma_j^2 \\
&\quad +b_j h_{i2} - (\gamma_i/2)\sigma_j^2)].
\end{aligned}
$$

The independence of error terms across periods derives the second line and the property of log normal distribution produces the third line. When $\ln x \sim N(m, s^2)$, it is known that $Ex = \exp(m + (1/2)s^2)$. In our case, $e = \ln x \sim N(m, s^2)$ thus $E\exp(e) = Ex = \exp(m + (1/2)s^2)$. The ordinal property of utility function results in (1.10).

Chapter 2

Compensating wage differentials among self-employed workers: Evidence from job satisfaction index

2.1 Introduction

Self-employed workers comprised 10.5% of the total U.S. workforce in March 1996.[1] Despite this large share of self-employed workers, self-employment has not attracted much attention among labor economists until recently, and the workings of the labor market among self-employed workers are still largely unknown. One of the remaining puzzles about self-employed workers is their lower earnings, which this paper attempts to explain with compensating wage differential theory. The compensating differential theory predicts lower earnings among self-employed workers when non-earnings aspects of self-employed job positively affect workers' utility. This paper directly tests the theory using job satisfaction scores available in the National Longitudinal Survey Youth 79 (NLSY79).

Several studies report lower earnings among self-employed workers as compared with their salaried and wage-earning counterparts.[2] For example, Hamilton (2000) found

[1] For recent trends of self-employment in the U.S., refer to Manser and Picot (1999).

[2] The analysis in the previous chapter described self-employed sector as the sector where the return to human capital is higher and consequently workers with higher human capital self-select into self-employment. In total, self-employed sector was described as better paid sector. At first glance, this chapter and the previous chapter may look contradicting, but if the utility from non-monetary aspects of self-employed job is introduced in the model of the previous chapter, then discussion in the previous chapter still carry over but we may observe lower earnings among self-employed workers. This can be

that self-employed workers earn less than salary/wage workers with similar, observable qualifications, using several measures of self-employed workers' earnings available in the Survey of Income and Program Participation (SIPP) 1984 panel. These lower earnings are mainly due to a lower growth in earnings among self-employed workers. According to Hamilton's findings, on average, self-employed workers with 10 years of business tenure earn 19% less than salary/wage workers with the same amount of work experience. Lower earnings growth among self-employed workers was also found by Lazear and Moore (1984). Krashinski (2000) found 10 to 30% lower median earnings among self-employed workers, except for college graduates, after controlling for observable workers' characteristics using CPS files over the period of 1979 - 1992. Carrington, McCue, and Pierce (1996) also found similar earning differences using the Current Population Survey (CPS) March files between 1967 and 1992.

These observed lower median and mean earnings among self-employed workers are rather puzzling, however, considering the self-employed workers' labor income risk as reported by Carrington, McCue, and Pierce (1996).[3] They found that self-employed workers' labor earnings are three times as sensitive to macro aggregates as salary/wage workers' and concluded that the labor earnings of self-employed workers are much more pro-cyclical to the business cycle. In addition, self-employed workers tend to use their own assets as capital for their own businesses due to liquidity constraints (Evans and Jovanovic (1989)) and, as a result, their labor earnings and asset income tend to co-move. This co-movement makes it difficult for self-employed workers to insure their future consumption, compared with wage/salary workers who can insure this by saving in a safe asset. In addition, Moskowitz and Vissing-Jorgensen (2001) showed self-employed workers tend to invest a large portion of their assets in their own businesses. As a result,

easily seen from Figure 1-1. If non-monetary aspects of self-employment generate utility, then indirect utility of SE - SE or SW - SE career from monetary income shifts down while total indirect utility stay constant. This shift may create lower average earnings among self-employed workers.

[3]Labor income risk among self-employed workers is intuitively appealing, and consequently several theoretical papers employ it as *an assumption* that characterizes self-employed jobs. See Kihlstrom and Laffont (1979) and Kanbur (1982) for example.

self-employed workers' portfolios are riskier than those of salary/wage workers, whose assets are invested in more diversified funds. Despite this risk, the average return on portfolios held by self-employed workers is almost equivalent to the average return on portfolios held by salary/wage workers. To compensate for this total income risk, at least at the first glance, the average of earnings for self-employed workers should be higher than that for salary/wage workers. In addition to income risks, self-employed workers enjoy fewer fringe benefits, such as employer-provided health insurance, than salary/wage workers, as pointed out by Hamilton (2000). Considering the negative aspects of self-employment, the lower earnings of self-employed workers is a puzzle.

Workers' negative self-selection into self-employment is one possible explanation for these observed lower earnings. If workers with negative unobserved characteristics self-select into self-employment, the lower earnings observed among self-employed workers may be due to these negative traits. To evaluate this possibility, Hamilton (2000) compared the earnings of two groups of salary/wage workers during a two year period; the first group consisted of workers who became self-employed workers in the second year, and the second group consisted of workers who continued to be salary/wage workers. He did not find any significant difference in salary/wage earnings for these two groups and concluded that self-selection does not explain lower earnings among self-employed workers. Krashinski (2000) did the same exercise using matched CPS data for 20 years and found no evidence o positive or negative selection into self-employment.[4] Borjas and Bronars (1989) even found positive self-selection into self-employment among white males, using a Heckman-style, self-selection correction method.[5] To summarize, previous research shows that negative self-selection into self-employment does not explain the

[4]Krashinski (2000) used this finding as evidence that self-employed workers are a good control group for testing the institutional hypothesis to explain wage inequality during the 1980s and 90s among salary/wage workers because self-employed workers are relatively free from institutional factors such as minimum wage restrictions and labor union involvement.

[5]The SMSA-level aggregate labor market conditions are used as instruments in the first stage selection equation. The variables are unemployment rate, population growth rate, crime rate, the level of local government expenditure, and the mean of income and education level. These variables are assumed to affect the labor market mobility but do not influence the determination of earnings.

lower earnings of self-employed workers.

Hamilton (2000) speculated the compensating differential as an alternative explanation. He claimed that self-employed workers enjoy non-earnings aspects of self-employment, such as being their own boss, and, accordingly, they accept lower earnings, although his claim was not supported by direct empirical evidence. In one significant study, Blanchflower and Oswald (1998) tested compensating differentials for self-employed workers using the job/life satisfaction variable available in British National Child Development Survey. Using cross section data from 1981 and 1991, they found that self-employed workers are more satisfied with their job/life than salary/wage workers. However, as authors admitted in their paper, there is a possibility that "self-employed people may be intrinsically more optimistic," and higher job/life satisfaction among self-employed workers might be due to intrinsic characteristics of self-employed workers. Several psychological studies, in fact, have revealed that people with positive attitudes toward life are more likely to be self-employed.[6] This problem arises from the interpersonal comparison aspect of the job/life satisfaction score that is determined by subjective perception. This problem can be resolved by considering the change of job satisfaction associated with changing jobs, because these satisfaction scores are compared within individuals. This possibility, however, cannot be explored without using panel data. In addition, contrary to the findings in Blanchflower and Oswald (1998), Clark and Oswald (1994), using a medical measure of psychiatric health, found that self-employed workers are more highly stressed than salary/wage workers.. Considering the risks that self-employed workers face, this result is not surprising. Thus, the evidence for the compensating differential among self-employed workers found in Blanchflower and Oswald (1998) is very informative but it does not decisively support the compensating differential hypothesis. This paper attempts to overcome the limitation of Blanchflower and Oswald (1998) by using panel data with a subjective job satisfaction measure (National Longitudinal Survey Youth 79), and, in addition, it attempts to calibrate the

[6]See Brockhaus and Horwitz (1986) for review of the literature.

monetary value of self-employment status.

The rest of this paper is organized as follows: Section 2 overviews the use of job satisfaction measures in economics. Section 3 briefly discusses our data and confirms the lower earnings of self-employed workers. Section 4 discusses job satisfaction scores in the data and implements a descriptive analysis. Section 5 describes a simple model of the compensating differential among self-employed workers and estimates the parameters of the model. Section 6 extends the analysis in Section 5, relaxing the imposed assumptions. Section 7 provides a summary and conclusion.

2.2 How Economists Have Used Job Satisfaction Measures

Economists often hesitate to use subjective job-satisfaction measures because linking job satisfaction measures with underlying utility is thought to be difficult.[7]

In the empirical literature, however, labor economists have made significant efforts to incorporate job satisfaction measures into economic analyses of labor market outcomes. There are roughly two ways in which job satisfaction is used in economic analyses of labor markets.

The first uses job satisfaction scores as an independent variable to examine the effect of job satisfaction on economic outcomes. Freeman (1978) showed that job (dis-)satisfaction predicts workers' job quitting behavior fairly well, even after controlling worker and job characteristics including their wages. Carrington, McCue, and Pierce (1996) and Clark (2001) obtained similar results using German and British data respectively. These findings establish that job satisfaction is a very informative economic variable. The method that is going to be applied to the data set in this study will help determine whether job satisfaction is a reliable economic variable. The results of the analysis will appear in data section of this paper.

[7]Job satisfaction is regarded as one of most important concepts by industrial and organizational psychologists, and textbooks in the field typically devote an entire chapter to job satisfaction and its effect on job performance. For example, see McCormick and Ilgen (1985) and Siegel and Lane (1987).

The second type of studies has analyzed the determination of job satisfaction, given that the job satisfaction variable is a reliable economic variable. The job satisfaction variable has been widely used to examine the effect of unionism on job satisfaction (Borjas (1979), Leigh (1979) and Bender and Sloane (1998)). Somewhat surprisingly, they typically found lower job satisfaction among union as compared with non-union workers. They explained this counter-intuitive finding as an evidence of an exit-voice mechanism of labor unions: even though workers are not happy with their jobs, they do not quit because their "voice" is heard through labor union.

Several studies have used job satisfaction scores to test the relative income concern hypothesis: job satisfaction is not only determined by individual earnings, but also by relative position of the earnings compared with workers who share similar characteristics (Hamermesh (1977), Clark and Oswald (1996), Hamermesh (2001)). All of these studies found evidence supporting the relative income concern hypothesis.

This review of literature shows how the use of job satisfaction in economics has extended the area on which economics can shed light.

2.3 Data and Lower Earnings among Self-Employed Workers

The National Longitudinal Survey Youth (NLSY79) is used in this study. The analysis sample consists of observations between 1985 and 1998 that was restricted to white male in order to be consistent with previous studies (Hamilton (2000), Krashinski (2000)). Individuals who work for money and are out of school are included in the sample. Individuals are dropped if their job classifications are unknown. The construction of the analysis sample is tabulated in Table 2 - 1.

As the first step of the analysis, the lower earnings of self-employed workers, which have been observed in previous studies, are replicated with this data. The following wage equation is estimated to see the earnings differentials between self-employed and salary/wage workers.

$$\ln w_{it} = \beta_0 + x_{it}\beta_1 + \beta_2 self_{it} + self_{it}x_{it}\beta_3 + c_i + e_{it} \ , \tag{2.1}$$

where w_{it} is hourly rate of earnings,[8] $self_{it}$ is the dummy that indicates self-employed, x_{it} is the vector of human capital and demographic variables, c_i is unobserved individual heterogeneity, and e_{it} is idiosyncratic error that satisfies $E[e_{it}|self_{it}, x_{it}, c_i] = 0$. The model is estimated through OLS assuming $[c_i|self_{it}, x_{it}] = 0$, and this assumption ensures that self selection into self-employment does not occur on the basis of unobserved characteristics. When the assumption $[c_i|self_{it}, x_{it}] = 0$ is violated through self-selection based on unobservables, the OLS estimator is biased. To deal with this possibility, the model is also estimated through a fixed effects estimation. The fixed effects estimator is unbiased if e_{it} is strictly exogenous (i.e. $E[e_{it}|self_i, x_i, c_i] = 0$, where $self_i = [self_{i1}, ..., self_{iT}], x_i = [x_{i1}, ..., x_{iT}]$); thus self-selection into self-employment based on time-constant unobserved characteristics is allowed.

The differences in earnings between salary/wage and self-employed workers are evaluated at 10 years of job market experience and 10 years of job (business) tenure.[9] The point of evaluation is important since the life-cycle earnings profile is much flatter among self-employed workers as pointed out in Lazear and Moore (1984).

The results of estimation and the estimated difference of earnings appear in Table 2 - 2. Both the results of OLS and the fixed effects estimation show that the earnings

[8] Hourly rate of pay is constructed by the Center for Human Resource Research (CHRR) based on respondents' usual earnings (inclusive of tips, overtime, and bonuses but before deductions). CHRR requests wages/salaries/tips income and business/firm income along with other income categories from both wage/salary workers and self-employed workers. Thus there is less concern that self-employed workers earnings contains capital income, in addition to labor income, which is the main concern for the measurement of income among self-employed when CPS is used. Therefore the measurement of earnings for self-employed workers in NLSY 79 is as good as those in SIPP that were used in Hamilton (2000). Although Hamilton (2000) also used the earnings that include capital gain as an alternative earnings measure of self-employed workers, I just focus on the labor earnings of self-employed worker here.

[9] Hamilton (2000) evaluated the differences at 10 years of tenure and 20 years of experience. However, in the sample used in this analysis, only 1.54% of total sample has more than 20 years of job experience. Thus the difference was instead evaluated at 10 years of experience. About half of the observations in the total sample have more than 10 years of experience and about 10 % of total sample has more than 10 years of job tenure.

of self-employed workers are higher without job experience or tenure as we can see from the positive coefficients for the self-employment dummy. However, the earnings-experience/tenure profiles are flatter for self-employed workers than for salary/wage workers. Because of the flatter earnings profile, self-employed workers with 10 years of job experience and 10 years of business tenure earn 14% ($t = -1.731$) to 23% ($t = 1.709$) less than salary/wage workers, depending on their educational background and marital status according to the OLS result. This result almost corresponds to the 19% self-employment penalty evaluated at 10 years of job (business) tenure and 20 years of experience found by Hamilton (2000) using labor income as self-employed workers' earnings.

According to the fixed effects result, however, self-employed workers with 10 years of job experience and 10 years of business tenure earn almost the same amount as salary/wage workers on average. This result may seem to imply an upward bias of the OLS estimator; however, careful examination of the estimated coefficients reveals that the difference between the OLS and fixed effects results mainly come from the difference in the estimated coefficient for the interaction of self-employment and education. The first difference estimates of the return to education, however, are not reliable because the earnings before attending school may not reveal full individual heterogeneity (see discussion in Card (2000)). In particular, self-employed workers can attend school while they work less, which results in lower earnings, and then then start to work at their full capacity after graduating, which ultimately results in higher earnings. Thus the fixed effects estimate for the return to education among self-employed workers may not be a reliable estimate and the conclusion instead should rely on OLS estimates.

To summarize the findings, self-employed workers earn less mainly due to a lower return to job experience and job tenure. When the difference is evaluated at 10 years of job experience and 10 years of job (business) tenure, self-employed workers earn 14% to 23% less of comparable salary/wage workers on average. Next I attempt to explain this earnings difference with the compensating earnings differential theory.

2.4 Job Satisfaction Scores and Descriptive Analysis

The main survey item used in this study is global job satisfaction. The question reads

> How [do/did] you feel about your job with [name of employer]? [Do/Did] you(1) like it very much, (2) like it fairly well, (3) dislike it somewhat, or (4) dislike it very much?(CODE ONE ONLY.)

The distribution of responses for this question is tabulated in Table 2- 3. The distribution remains nearly constant over time. Examination of Table 2- 3 reveals that bout 65% of self-employed workers chose "like it very much" while only about 45% of salary/wage workers chose this answer. It is also noTable 2- that only about 3-5% of self-employed workers chose "dislike" ("dislike somewhat" and "dislike very much" combined.) while around 8-10% of salary/wage workers chose this answer. This rough examination of the distribution clearly indicates that self-employed workers are more satisfied with their jobs.

Before developing a detailed discussion of the compensating earnings differential based on job satisfaction scores, I examine whether this score is a meaningful economic variable. If the job satisfaction score contains meaningful information about a worker's actual job satisfaction, the score should predict the observed worker's behavior, in particular, the worker's future job change.

Table 2- 4 tabulates the probability of job change between time t and $t-1$ classified by the job satisfaction at time $t-1$. This Table 2- clearly tells us that the worker who dislikes his/her job is more likely to change his/her job.

Since the probability of job change may depend on the worker's demographic characteristics that may be correlated with job satisfaction, a probit model in which the probability of job change depends on demographic variables as well as job satisfaction is estimated. The results of the probit estimation appear in Table 2 - 5, Column 1. The results indicate that those who dislike their jobs very much are 22% more likely to change their jobs than those who like their jobs very much. The inclusion of control variables hardly changed the results obtained in Table 2- 4. I have also tried the specification that included lagged log wage as an independent variable, as used in Clark (2001). The estimated results for this specification appear in Table 2- 5, Column 2. The results indicate that a 10% increase in hourly earnings decreases the probability of job change by 0.26%. The size of this effect is relatively small compared with the effect of job satisfaction on job change. For example, changing job satisfaction from "like somewhat" to "like very much" decreases the job change probability by 10.8% (=0.231-0.123). This larger effect of job satisfaction on job change than wage effect can be explained as follows. If the job match quality is more significant in job satisfaction determination than in wage determination, job satisfaction is a more crucial determinant of job change than wage because workers have a greater chance to improve their job satisfaction but less chance to improve their wage through job change. This relatively small effect of hourly earnings on job change compared with job satisfaction was also found in Clark (2001), although the result in his study was not this extreme. We should also notice that the size of the coefficients for job satisfaction dummies hardly changed due to inclusion of log of hourly earnings.

The results obtained from Table 2- 4 and Table 2- 5 clearly indicate that the job satisfaction score contains valuable information about the worker's actual satisfaction in his or her job.

One of the main drawbacks of using the job satisfaction score, as noted in the previous literature, is the difficulty in the interpersonal comparison of subjective measures. This study attempts to overcome this difficulty by using panel data because panel data t enables the researcher to examine the change in job satisfaction associated with job change. In the following analysis, the job satisfaction score is assumed to be comparable within each individual over time. This assumption is much weaker than the assumption of interpersonal comparability of subjective measures.

As a simple way to examine the change in job satisfaction associated with job change, the transition matrices of job satisfaction for job stayers and job changers appear in Table 2- 6. Findings from these matrices are summarized as follows:

- Among job stayers, self-employed workers are more likely to stay in the "like very much" category as compared with wage/salary workers. (Panel A and Panel B)

- Job changers who move from salary/wage jobs toself-employed jobs are more likely to experience a positive transition of job satisfaction than job changers who stay in salary/wage jobs. It is also noTable 2- that job changers' job satisfaction as salary/wage workers are originally slightly higher than stayers'. This may be evidence of self-selection. (Panel A and Panel E)

- This positive transition of job satisfaction is less likely to occur among those who change from self-employed jobs to wage/salary jobs. Moreover, about 20% of job changers experience a *negative* transition of job satisfaction. (Panel F)

These findings suggest the conclusion that self-employed jobs are more satisfying than salary/wage jobs. However, other demographic characteristics that also might affect job satisfaction, such as marital status, may vary at the time of job change and this might result in the findings above. To address this possibility, the effects of workers' observed and unobserved characteristics on job satisfaction are controlled in the following analysis. In addition, I attempt to calculate the monetary value of self-employment status in terms of job satisfaction.

2.5 Compensating Differentials among Self-Employed Workers

To test the compensating differential hypothesis among self-employed workers, this section attempts to calculate the monetary value of self-employment status in terms of job satisfaction to see if it is large enough to explain the earnings differential between salary/wage workers and self-employed workers.

A straightforward way to see whether the difference in job satisfaction between self-employed job and salary/wage job explains the difference in earnings is to estimate the following equation:

$$\ln w_{it} = \beta_0 + x_{it}\beta_1 + \beta_2 self_{it} + x_{it} + \beta_3 js_{it} + e_{it} \ , \tag{2.2}$$

and see if $H_0 : \beta_2 = 0$ hold. If the null hypothesis is not rejected, then we can conclude that the difference in earnings originated from job satisfaction, not from self-employment status. However this obvious method neglects the fact that job satisfaction is also the function of earnings, as shown in previous studies. This endogeneity biases the estimates of β_3 upward because js_{it} and e_{it} are positively correlated. This bias causes a downward bias in the estimates of β_2 since job satisfaction and self-employment status are positively correlated, as we saw in the previous section. This downward bias may result in the false acceptance of the null hypothesis. Thus, this avenue is not pursued in this paper.

Instead, I examine how self-employment status and earnings affect job satisfaction to see whether the compensating earnings differential explains lower earnings among self-employed workers. To calculate the monetary value of self-employment status in terms of job satisfaction, the marginal rate of substitution between self-employment status and monetary earnings in terms of job satisfaction is calculated. The link between the job satisfaction score and utility is specified as

$$js_{it} = \begin{cases} 4 & \text{if } js_{it}^* \geq \mu_3, \\ 3 & \text{if } \mu_3 > js_{it}^* \geq \mu_2, \\ 2 & \text{if } \mu_2 > js_{it}^* \geq \mu_1, \\ 1 & \text{if } \mu_1 > js_{it}^*, \end{cases} \tag{2.3}$$

where js_{it} is a categorical variable indicating worker i at time t's response to the job satisfaction question (1: "Dislike Very Much" - 4:"Like Very Much"), whereas js_{it}^* is the latent continuous variable of job satisfaction and $\mu_k (k = 1, 2, 3)$ are the thresholds of job satisfaction that determine the answer for the job satisfaction question. Although many factors may affect a worker's job satisfaction, to see the tradeoff between self-employment status and monetary compensation, those two factors are mainly considered as the determinants of job satisfaction. To estimate the monetary value of self-employment status in terms of job satisfaction, three additional assumptions are imposed.

First, as a shape of job satisfaction function, a linear function is assumed as a first order approximation. Several demographic variables are also assumed to affect job satisfaction. Moreover, other factors that may affect job satisfaction are assumed to be independent of self-employment status, monetary compensation, and demographic variables, and thus these factors are assumed to be normally distributed. This assumption results in

Assumption 1 (Linear job satisfaction function)

$$js^*_{it} = \theta_0 + \theta_1 s_{it} + \theta_2 \ln w_{it} + x_{it}\theta_3 + c_i + e_{it}, \quad e_{it}|s_{it}, w_{it}, x_{it}, c_i \sim N(0, 1) \; , \tag{2.4}$$

where s_{it} is the dummy variable for self-employment status, w_{it} is hourly rate of pay, x_{it} is the vector of a worker's attributes, and c_i is individual heterogeneity in utility level. Specifically x_{it} contains a marital status dummy; a sex dummy; age, racial or ethnic group dummies; educational background; labor market experience; and job (business) tenure.

The next step is to calibrate the monetary value of self-employment status in terms of job satisfaction. As a measure of monetary value, we can calculate how much workers can give up in terms of salary/wage earnings in exchange of one dollar earnings as a self-employed worker while keeping their job satisfaction constant. The α in the following equation gives this ratio of trade off:

$$\underbrace{\theta_2 \ln(\alpha w_{it}) + x_{it}\theta_3 + c_i + e_{it}}_{js^* \text{ of a salary/wage worker}} = \underbrace{\theta_1 + \theta_2 \ln w_{it} + x_{it}\theta_3 + c_i + e_{it}}_{js^* \text{ of a self-employed worker}} . \tag{2.5}$$

When a worker receives α dollars of earnings per hour as a salary/wage worker, the worker has the same level of job satisfaction when the worker earns one dollar per hour as a self-employed worker. The solution for the equation is simply, $\alpha = \exp(\theta_1/\theta_2)$. In other words, α dollars of earnings as a salary/wage worker is equivalent to one dollar of earnings as a self-employed worker. This value, α, is reported as a monetary value of self-employment status in terms of job satisfaction.

To simplify the econometric model, two additional assumptions that will be relaxed later are made:

Assumption 2 (Independence of Heterogeneity)

$$c_i \perp s_i, w_i, x_i \ . \tag{2.6}$$

where $s_i = [s_{i1}, s_{i2}, ..., s_{iT}]$, $w_i = [w_{i1}, w_{i2}, ..., w_{iT}]$ and $x_i = [x_{i1}, x_{i2}, ..., x_{iT}]$. This assumption assures that individual heterogeneity is independent of observables and that the heterogeneity does not cause any inconsistency of the pooled, ordered probit estimator.

Assumption 3 (No feedback from current job satisfaction shock to future self-employment status)

$$e_{it}|s_i, w_i, x_i, c_i \sim N(0,1) \ . \tag{2.7}$$

This assumption rules out the feedback from current shock on job satisfaction to future self-employment status through job change, since if the feedback exists, the distribution of current e depends on future s.

These three assumptions result in the pooled, ordered probit model, and the parameters in (2.4) can be estimated. To estimate the model, I dropped the observations whose hourly rate of pay were either above the 99 percentile or below the 1 percentile in each year, and this sample selection results in sample (5) in Table 2- 1. Since those who earned extremely high wages and were extremely satisfied with their jobs could only report "like their job very much" at the maximum and vice versa for low wage earners, including those extreme earners would attenuate the coefficient on hourly rate of pay toward zero and this would make the estimates of the monetary value of self-employment status upwardly biased.[10] The results of estimation appear in Table 2- 7, Column 1 and

[10] I tried several trimming rules. The results were not essentially changed when I applied 5%-95% or

Column 2. The result that appears in Column 1 is the specification that only includes the self-employment dummy and the log of hourly wage as independent variables. The coefficient for self-employment is 0.486. The size of the coefficient is not large enough to change the worker's response to the job satisfaction question from "dislike very much" to "like somewhat" or from "dislike somewhat" to "like very much," since the critical values of the ordered probit are -0.377, 0.360, and 1.891. However, the size of the coefficient is much larger than the coefficient for log earnings. The coefficient for log earnings is 0.248, which is surprisingly small if we compare this value with the critical values. Due to this small effect of earnings on job satisfaction, one-dollar earnings of self-employed workers are evaluated as more than seven dollars of salary/wage workers' earnings. This value is large enough to compensate for the lower earnings among self-employed workers whose earnings are about 20% lower than salary/wage workers' when workers have 10 years of job experience and 10 years tenure.

When marital status, educational attainment, and job experience are included in the specification, the coefficient for earnings becomes even smaller because a part of high earnings is explained by the added explanatory variables. In this specification, the estimated monetary value of self-employment status becomes $\alpha = 818$; one dollar earnings as a self-employed worker is equivalent to \$8.18 earnings as a salary/wage worker. Again, this puzzling result is obtained due to the small effect of earnings on job satisfaction while the effect of self-employment status is large.

2.6 Extensions

A surprisingly large estimate of the monetary value of self-employment was obtained in the previous section. Now, I consider several possible reasons why the effect of self-employment status on job satisfaction may be overestimated. To do so, I will relax the assumptions made so far one by one in this section. As partly suggested in the analysis of transition matrices of job satisfaction, workers who become self-employed seem

10%-90% rules.

to have a positive attitude toward their jobs independent from self-employment status. If this is the case, the coefficient for self-employed workers was overestimated in the pooled probit model, since c_i and s_{it} are positively correlated. In addition, if workers with high ability have high expectations for their earnings, workers with high ability are less happy with their current earnings. As a result, unobserved heterogeneity and current earnings, which is a proxy for ability, may be negatively correlated and the coefficient for hourly rate of pay may be negatively biased. Considering this heterogeneity or other possibilities that unobserved heterogeneity in job satisfaction are dependent upon observable characteristics, *the assumption 2* (Interpersonal comparability of job satisfaction) is replaced with

Assumption 2' (the "Fixed Effects" assumption)

$$c_i|s_i, w_i, x_i \sim N(\gamma_1\bar{s}_i + \gamma_2\overline{\ln w_i} + \gamma_3\bar{x}_i, \sigma_c^2). \tag{2.8}$$

This assumption allows dependence between c_i and s_i or x_i in a restrictive way,[11] where $\bar{s}_i$, $\overline{\ln w_i}$ and $\bar{x}_i$ are mean of s_i, $\ln w_i$ and x_i respectively.[12] The consistent estimators are obtained through a pooled, ordered probit estimation of the model that includes individual means of independent variables. The importance of assumption 3 should be emphasized here. If current shock to job satisfaction, e_{it}, affects the future value of self-employment status through job change behavior, e_{it} and $\bar{s}_i$, which is one of the independent variables and dependent on the future self-employment status, is dependent and a consistent estimator cannot be obtained.

The results of estimation appear in Table 2- 6, Column 3. The coefficient for self-employment decreases as expected from the positive correlation of c_i and s_{it}.At the same time, the coefficient for earnings increased due to negative correlation of c_i and $\ln w_{it}$. As a result, the calculated monetary value of self-employment status becomes 284% of earnings.

[11] Mundlak (1978) proposed a variant of this assumption in a linear regression framework.

[12] The analysis under this assumption is called a fixed effect analysis because this assumption allows dependent unobserved heterogeneity..

As confirmed in the previous section and in previous studies (Freeman (1978), Clark, Georgellis, and Sanfey (1998) and Clark (2001)), job changes tend to follow low job satisfaction. In the light of this fact, ruling out the feedback from e_{it} to $s_{it-1}, \ldots s_{iT}$ is a strong assumption. In particular, if a salary/wage worker experiences low job satisfaction because of some shock (after conditioning on individual heterogeneity) and become a self-employed worker, we tend to overestimate the effect of self-employment on job satisfaction because a salary/wage workers with current negative shock is more likely to be self-employed in the following period. To take care of this possibility, feedback effects are allowed through the assumption,

Assumption 3' (Feedback effect)

$$e_{it}|s_i, x_i, a_i \sim N(h(s_{it}, s_{it+1}, \ldots s_{iT}), 1), \qquad (2.9)$$

where $h(s_{it}, s_{it+1}, \ldots, s_{iT}) = \delta_1 \max(|s_{it-\tau} - s_{it+\tau-1}|, \ldots, |s_{it-1} - s_{it}|)$. This function indicates that if a change in self-employment status takes place within τ years due to current shock on job satisfaction, the parameter τ is the maximum lag period of the feedback from e_{it} on future job change. For example, if $\tau = 3$ then the feedback is assumed to take place within 3 years. The cases $\tau = 1, 2$ and 3 are considered in the following analysis. The model is estimated with a pooled, ordered probit model with an individual mean of independent variables and $h(.)$ as independent variables.

The estimated results of the "fixed effects" probit model with feedback effects appear in Table 2- 7, Columns (4) - (6). The estimated coefficients for the feedback term, $h(.)$, are all negative but they are not significant in all specifications. Negative coefficients imply that a current negative shock on job satisfaction causes a change in self-employment status through a job change. However, even after considering correlated heterogeneity and feedback from job satisfaction to future job changes, we find essentially similar results as before: The estimated monetary value of self-employment status is about 390%. Since the coefficients for the feedback terms are not significantly different from zero, I take the fixed effects estimate, which is $\hat{\alpha} = 3.387 (s.e. = 0.697)$, as the most preferable estimate for the monetary value of self-employment status in terms of job satisfaction.

Now, the very high valuation of self-employment status is the puzzle that should be explained. Although self-employed workers with 10 years of job experience and 10 years of business tenure earn about 20% less than their salaried/wage-earning counterparts, the estimated results imply that one dollar of earnings as a self-employed worker is equivalent to three to four dollars earned as a salary/wage worker in terms of job satisfaction.[13] If we consider job satisfaction as equivalent to utility, this value means that self-employed workers do not move to salary/wage jobs even when they are offered three or four times more than their current earnings, but this finding is counterintuitive. However, there are four explanations that may explain these surprising findings.

The first is the fact that job satisfaction is only a segment of utility function. Suppose the simplest form of utility function, which consists of only consumption and job satisfaction:

$$u(c(w), js(se, w)) \quad , \tag{2.10}$$

where c is consumption that is presumably a function of earnings. Then the marginal rate of substitution between self-employment status and earnings is

$$MRS = \frac{\frac{\partial u}{\partial se}}{\frac{\partial u}{\partial w}} = \frac{u_{js} \cdot js_{se}}{u_c \cdot c_w + u_{js} \cdot js_w} \quad , \tag{2.11}$$

where f_x denotes the partial derivative of f with respect to x. Since $u_c > 0$ and $c_w > 0$, the monetary value of self-employment in terms of job satisfaction, which is (js_{se}/js_w), overstates the value of self-employment status in terms of *utility*. Although the monetary value of self-employment status in terms of job satisfaction has been estimated in this paper, the monetary value of self-employment status in terms of utility should be estimated to appraise the validity of the compensating differential hypothesis. However, calculating the monetary value of self-employment status in terms of job satisfaction is a useful exercise in light of the reality that a numerical measure of utility is not available.

[13] Although I tried several specifications in which the monetary value depended on job experience and tenure, the result virtually did not change.

The second explanation concerns the overestimation of success among self-employed workers. Empirical studies have found that self-employed workers are overly confident in their future success as compared with salary/wage workers (Cooper, Woo, and Dunkelberg (1988) and Arabsheibani, deMeza, Maloney, and Pearson (2000)). For example, Arabsheibani, deMeza, Maloney, and Pearson (2000) report that self-employed workers expect better financial outcomes in the following year than salary/wage do, even though they, in fact, experience worse outcomes. When self-employed workers expect future monetary success, self-employment status has a subjective "option" value for future earnings and this option value may make self-employed workers more satisfied with their jobs. Although this effect is attributed to the non-monetary value of self-employment status in this study, it instead should be attributed to the monetary value of self-employment status. This overestimation of the non-monetary aspect and underestimation of the monetary aspect result in an overestimation of the non-monetary aspect of self-employed jobs in terms of job satisfaction.

The third explanation relates to underreporting in self-employed workers' earnings; if this is the case, the value of self-employment is overestimated, since the utility from underreported earnings is captured through self-employment status. Although NLSY makes good efforts to collect reliable labor income from self-employed workers, self-employed workers may refer to their tax forms from previous year in which earnings were underreported for tax avoidance purposes when they answer earnings questions. For example, Joulfaian and Rider (1998) show that the underreport rate of self-employed earnings is about 20% on average, using the Taxpayer Compliance Measurement Program.[14] Also, self-employed workers may consume out of business expenses. For example, they may drive company-owned cars for personal purposes. This also may increase the monetary value of self-employment status, but it should not be interpreted as a compensating differential since it simply captures consumption.

[14] The Taxpayer Compliance Measurement Program data are stratified samples of individual tax returns subject to intensive line-by-line examinations (Joulfaian and Rider (1998)).

The fourth explanation relates to i heterogeneity in the marginal job satisfaction from self-employment. When heterogeneity is explicitly modeled, the utility function becomes

$$
\begin{aligned}
js^*_{it} &= \theta_0 + \theta_{1i} s_{it} + \theta_2 \ln w_{it} + x_{it}\theta_3 + c_i + e_{it}, \\
&= \theta_0 + \bar{\theta}_1 s_{it} + \theta_2 \ln w_{it} + x_{it}\theta_3 + c_i + v_{it}, \\
v_{it}&|s_{it}, w_{it}, x_{it} \sim N((\theta_{1i} - \bar{\theta}_1)s_{it}, \sigma_e). \qquad (2.12)
\end{aligned}
$$

Marginal job satisfaction and self-employment θ_{1i}, and s_{it}, are likely to have a positive correlation since those who gets higher job satisfaction from self-employment are more likely to be self-employed, consequently, s_{it} and the error term is positively correlated and plim$\hat{\bar{\theta}}_{1i} > \bar{\theta}_1$. Thus the pooled, ordered probit estimator overestimates the *average* of θ_1. This positive correlation can be very large for workers who want to be self-employed at any cost. Thus the calculated monetary value of self-employment from the pooled probit model can be interpreted as the upper bound of the *average* evaluation of self-employment throughout the population. In addition, the entry to self-employment continues so long as a worker's evaluation of self-employment status is above the earnings penalty of self-employed workers. Thus, the earnings penalty of self-employed workers is determined at the *margin* through a market mechanism. It is no surprise to find a higher *average* evaluation of self-employment status than the evaluation of self-employment status by the last worker who *marginally* becomes a self-employed worker.

The interpretation of the monetary value of self-employment status becomes more restricted for the fixed effects model. The coefficient θ_{1i} is identified as those who changed self-employment status during the sample period since if s_{it} is constant over sample period, the variable is perfectly multicolinear with $\bar{s}_i$ and only $\theta_{1i} + \gamma_1$ is identified for those observations. Thus the estimated monetary value of self-employment status from the fixed effects model is the average evaluation of self-employment status among workers who experience a transition between a salary/wage job and self-employed job. As we can see from Table 2- 6, there are more observations that transit from a salary/wage job to a self-employed job, so it is not surprising to find higher evaluations of self-employment status among workers who become self-employed during the sample period. Those who leave self-employment might also do so because of financial reasons but not because of job satisfaction.

These four considerations may well reconcile the estimated self-employment penalty (20% of earnings for a worker with 10 years of job experience and 10 years of job tenure) with the estimated monetary value of self-employment jobs (300% - 400%) in term of job satisfaction.

2.7 Conclusion

Analysis of job satisfaction scores show that self-employed workers are more satisfied with their jobs than salary/wage workers. Moreover, one dollar of earnings while a self-employed worker is equivalent to three to four dollars of earnings while a salary/wage worker in terms of job satisfaction. This finding is preserved even when individual heterogeneity, which is potentially correlated with self-employment status, and the feedback effect, which runs from current job satisfaction to future job change, are considered.

This high valuation of self-employment status in terms of job satisfaction may overestimate the actual trade-off between self-employment status and monetary income in terms of utility. However, even after taking the effect of unavoidable overestimation into consideration, the value of self-employment status in terms of job satisfaction, which is 300 to 400% of other workers' earnings, seems high enough to explain the lower earnings of self-employed workers. Thus, the results obtained in this paper support the compensating differential hypothesis as an explanation for lower earnings among self-employed workers.

Promising future research would develop a rigorous appraisal of the compensating wage differential hypothesis by using a better measurement of utility or principals of revealed preference.

Chapter 3

Peer effects on substance use among American teenagers

3.1 Introduction

Widespread use of illicit substances by American teenagers attracts both public attention and research interest. The changing percentages of substance users during the 1990s are plotted in Figure 2-1. Although the percentage of alcohol users dropped in the early 1990s, it still remains high. This figure shows the steady trend of cigarette users at a high level.[1] It is also notable that the percentage of marijuana users increased from 4.4% to 9.7% between 1990 and 1997.

These figures have sparked much public interest about the reasons why teenagers use substances and what policy makers can do to reduce this usage. Besides the price of substances, peer effects or peer pressure is identified as a critical determinant, since the use of substances is considered to be a highly social behavior.[2]

Reacting to this interest, economists and sociologists have tried to estimate the existence and the strength of peer effects. Identifying peer effects is not easy since an observed behavior shared by a teenager and his/her peer may result from unobserved factors that group members share instead of peer effects. In addition, identifying peer

[1]On the other hand, Gruber (2000) reports that the percentage of cigarette smokers increased by one-third between 1991 and 1997. (Based on youth behavior risk survey, for 9th through 12th graders, the number has increased from 27% to 36% between 1991 and 1997.)

[2]See Los-Angeles-Times (1999) for interviews of youth smokers on the reasons why they smoke.

effects becomes complex when the average reference group's outcome is used as a measurement of peers' behavior. Determining whether a teenager's behavior affects his/her peers or vice versa is difficult. Manski (1993) articulated this as the "reflection problem." In addition, both current substance users and backgrounds of group members may affect individual behaviors. Although both effects are called peer effects, each has different policy implications. Distinguishing between these two effects, however, is known to be difficult (Manski (1993)).

This paper employs a critically different strategy for identifying peer effects; I identify peer effects by using teenagers' subjective perceptions. Manski (1993) wrote:

> Given that identification based on observed behavior alone is so tenuous, experimental and subjective data will have to play an important role in future efforts to learn about social effects.

Using subjective perceptions of peer behaviors, identifying peer effects is free from the problems that arise with using an average outcome as a peer variable. According to Manski (2000), this approach has not been taken seriously since he originally suggested it in 1993.

In addition, I employ school and household fixed effect estimation to ensure the robustness of my results.

3.2 Reflection problem

Manski (1993) articulated several issues concerning the identification of peer effects using an average group outcome as a peer variable. A short sketch of the problem follows. Let y be an outcome of interest, x be attributes characterizing an individual's reference group and z be attributes that affect the outcome directly. The outcome is characterized by

$$y = \alpha + \beta E(y|x) + E(z|x)\gamma + z\eta + u, \quad E(u|x, z) = x\delta. \tag{3.1}$$

If $\beta \neq 0$, then an individual behavior is affected by the mean of the group outcome, $E(y|x)$. This is the "endogenous effect." If $\gamma \neq 0$, an individual behavior is affected by the group mean of the exogenous variable (background of group members); this is the "contextual effect." If $\delta \neq 0$, the model exhibits the "correlated effect." People in the same group behave similarly because their shared group characteristics are correlated with unobservable factors, such as social institutions.

Taking conditional expectation on z and x, the model becomes

$$E(y|x, z) = \alpha + \beta E(y|x) + E(z|x)\gamma + z\eta + x\delta. \tag{3.2}$$

To discuss the identification of parameters, we need to solve for the conditional expectation of y in terms of x and z. Using the iterated law of expectations,

$$E(y|x) = \alpha + \beta E(y|x) + E(z|x)\gamma + E(z|x)\eta + x\delta. \tag{3.3}$$

Solving the expression for $E(y|x)$ and substituting it into (3.2), we obtain

$$E(y|x, z) = \alpha/(1-\beta) + E(z|x)[(\gamma + \beta\eta)/(1-\beta)] + x\delta/(1-\beta) + z\eta. \tag{3.4}$$

The composite parameters are identified if $[1, E(z|x), x, z]$ are linearly independent.[3]

Even if the linear independence is assured, the endogenous effect (β) is not identified if the contextual effect is present (i.e. $\gamma \neq 0$). As Manski (1993) stressed, distinguishing the endogenous effect from the contextual effect is important because these two effects have critically different policy implications. Consider, for example, that a lecture on the health effects of smoking is provided to one class but not to the other classes in a particular school. If the lecture effectively makes students quit smoking in the class,

[3]The linear independence of explanatory variables is violated if

1. z is a function of x since $E(z(x)|x) = z(x)$. Consequently $E(z|x)$ and z are linearly dependent. This case occurs in the situation when group members share the same exogenous variables.
2. z does not vary with x. Since $E(z|x)$ is constant, $E(z|x)$ and z are linearly dependent. This case occurs if average exogenous variables are identical across groups.
3. $E(z|x)$ is a linear function of x since $E(z|x) = \theta x$. This is a theoretical possibility rather than an actual possibility since x is usually an index for a group.

the effect propagates to the students in the other classes through the endogenous effect. If the endogenous effect does not exist, the effect of the lecture is limited to the class where the lecture is given. While the endogenous effect implies this "social multiplier," the contextual effect and the correlated effect do not imply that.

Moreover, Manski (1993) warned that, in general, sample correspondence of $E(y|x)$, denoted by $E_N(y|x)$, is not identical to $E(y|x)$. As a result, $\hat{\beta}$ can be calculated in the sample, even if β is not identified in the population. Thus, the successful calculation of $\hat{\beta}$ does not imply anything about the identification. After all, the identification of the mixture of the endogenous effect and the contextual effect is possible under the assumption of the linear independence of $[1, E(z|x), x, z]$. Distinguishing between the endogenous effect and the contextual effect is, however, principally impossible.

The difficulty of the identification arises because the mean of the outcome is used as an explanatory variable. I avoid this complication in this study since the direct subjective perceptions of peers' behavior, instead of the average behavior of peers, is the key explanatory variable. The beauty of this approach is that, once the linear independence assumption of explanatory variables is assured, the endogenous effect and the contextual effect are *separately* identified. In the next section, the model with subjective perception is discussed.

3.3 The model with perceived peer behaviors

The model with perceived peer behaviors is specified as follows:

$$y = \alpha + \beta p + E(z|x)\gamma + z\eta + u, \tag{3.5}$$

where y is an outcome of interest, x is attributes characterizing an individual's reference group and z is attributes that affect the outcome directly. The variable p is subjective perception of peer behaviors. Once $E(u|p, z, x) = 0$ and linear independence of $[1, p, z, E(z|x)]$ are assured,[4] the parameters, α, β, γ and η, are identified through OLS.

[4]The assumption of linear independence here is more restrictive than the assumption needed in Manski (1993), since p is newly added to the list of variables which should be linearly independent.

Since the group average of observed behaviors is not used as an explanatory variable as in Manski (1993), no complication of identification arises.

The crucial assumption in this model is that perceived rather than actual peer behaviors determine individual behaviors. This assumption is consistent with the conformist model. Akerlof (1997) argued that individuals get utility from behaving like an "average" person in a reference group. It is natural to assume that perceived peer behaviors produce the image of the "average" person. This "conformist" behavior may be reinforced through the formation of group norms. By forming group norms that require members to engage in similar behaviors, each individual group member enjoys higher utility. Becker (1996) considered a utility function (U) that has own norm (N) and norm of peers (N_P) as arguments and its cross derivative to be positive ($\partial^2 U/(\partial N \partial N_P) > 0$). Thus individuals can obtain higher utility through forming their own norms similar to the group norm. It is natural again to assume that each individual perceives group norms through perceived peer behaviors. Individuals behave according to their norms. To summarize, the assumption that perceived peer behaviors determine individual behaviors is a natural one if peer effects operate through "conformist" preferences or the enforcement of group norms.

At the same time, there are many other reasons why peer effects exist. For example, American kids play baseball instead of cricket since other kids know how to play baseball, and, consequently, it is easier to find playmates. Moreover, since playing an actual game would be much more fun than playing catch, it may be an important goal for kids to find many playmates easily. In this example, utility obtained from playing baseball depends on the number of players with whom a kid plays (up to 18 players). By the same token, teenagers may obtain higher utility from tobacco if they consume it with their friends. In these situations, actual peer behaviors, rather than perceived ones, affect an individual's behaviors. Although this possibility cannot be ruled out, it is simply assumed that an individual behavior is influenced only by the perceived peer behaviors.[5] Relaxing this

[5] Of course, the actual peer behaviors may determine perceived peer behaviors; however, here I

assumption causes complication in identifying the endogenous effect as noted earlier. Thus, the interpretation of the endogenous effect in this paper should be restricted by this assumption.

3.4 Literature review

Many papers shed light on peer effects. In this section, the papers are classified by the identification strategy used. The identification of the endogenous effect is especially focused because of its unique policy implication of the "social multiplier." A thorough review of the existing literature reveals the strengths and weaknesses of each identification strategy. In particular, the limitation of an identification strategy that only uses observed behavior becomes clear.[6] I also introduce the studies that use economic theory to help provide additional insights into the identification of the endogenous effect. It should be noticed that each study does not necessarily fall into a single category since several identification strategies may be used in any given paper.

3.4.1 Identification through proxy variable

Several studies use variables that represent "peer quality" or "neighborhood quality." The problem of whether the endogenous effect can be identified using these proxy variables is considered. The outcome of interest (teenage pregnancy and high school dropping out in Evans, Oates, and Schwab (1992) and high school dropping out in Crane (1991)) is characterized by

$$y = \alpha + \beta E(y|x) + z\eta + u. \tag{3.6}$$

assume that once perceived peer behaviors are included in the behavioral equation, the equation does not include actual peer behavior.

[6]Many of studies surveyed in this section used nonlinear models such as probit. However, we discuss identification strategies in the context of linear models, since the discussions of identification fundamentally carry over. Moreover, the identification of parameters should not depend only on the nonlinearity assumption. The sizes of peer effects in those studies are discussed in terms of marginal effects.

Since two of studies above implicitly assume absence of the contextual effect, I also adopt that assumption. Instead of $E(y|x)$, however, a proxy variable, such as the portion of students who is eligible for a school free lunch program (Evans, Oates, and Schwab (1992)) or a neighborhood occupational structure (Crane (1991)),

$$q = E(y|x) + v \tag{3.7}$$

is used in the estimation. The equation actually estimated reduces to

$$y = \alpha + \beta q + z\eta + u - \beta v \tag{3.8}$$

The assumptions $E(u|x, z) = 0$ and $E(v|x, z) = 0$ are required for the identification of the endogenous effect, β. Assuming the absence of the correlated effect, the first assumption is assured. On the other hand, the second assumption is questionable. Since q in these studies consists of variables defined on reference groups, q are naturally functions of x. As implied by (3.7), v is a function of x accordingly. Thus, $E(v|x, z) \neq 0$. Although using proxy of $E(y|x)$ reveals something about broadly defined peer effects, identifying the endogenous effect is impossible using a proxy variable.

3.4.2 Identification assuming the absence of the contextual effect

Many studies of peer effects fall into this category. Case and Katz (1991) looked at the effect of neighborhood average incidence on youth behavior, including drug use. Sacerdote (2000) looked at the effect of randomly assigned roommates in a college dormitory on student outcomes such as GPA. Gaviria and Raphael (2000)) looked at peer effects within schools on students' behavior.[7]

These studies try to identify the structural parameters in (3.2). As we have seen in (3.4), the endogenous effect (β) cannot be identified without assuming absence of the contextual effect (i.e. $\gamma = 0$). Consequently, all of these studies assume the absence

[7]The behaviors considered in Gaviria and Raphael (2000) are substance uses, church attendance, and dropping out of high school

of the contextual effect except for Sacerdote (2000).[8] Replacing the population mean $E(y|x)$ with the sample average $E_N(y|x)$, the (3.2) is estimated assuming $\gamma = 0$. The assumption $\gamma = 0$ is not severe if the research interest lies in examining broadly defined peer effects. However, if the existence of the "social multiplier" is the main concern, the assumption is restrictive, since all of the observed peer effects are attributed to the endogenous effect by assumption. Thus the identification based on $\gamma = 0$ is not appropriate for deriving policy implications since the impact of policy intervention depends on the existence of the "social multiplier."

Most of the studies mentioned earlier were concerned about the violation of $E(u|x, z) = 0$ and the consequent bias in the OLS estimator. Unobserved group characteristics (e.g. teachers' competence in a school) make $E(u|x, z)$ a function of x (the correlated effect). This correlation of x and u makes the OLS estimator of β biased since $E(y|x)$ is also a function of x. Alternatively, unobserved individual characteristics correlated with observed characteristics make $E(u|x, z)$ be a function of z. This correlation makes the OLS estimator of η biased and the bias could be transmitted to the estimator of β. For the latter concern, IV estimation implied by (3.3) solves the problem. Under assumption $\gamma = 0$, $E(z|x)$ is excluded from the behavioral equation of interest (3.2) but correlated with $E(y|x)$ given $\eta \neq 0$; thus $E(z|x)$ serves as instruments for $E(y|x)$. An important point here is that u is allowed to be correlated with z but not with x. If u is correlated with x, $E(z|x)$ is correlated with u and cannot be an IV.

Evans, Oates, and Schwab (1992) considered the case in which u includes parents' "willingness" to invest in their children when this willingness affects where the family resides (x) so that the parents choose peer quality ($E(y|x)$) endogenously. In this situation of endogenous sorting, u and x are correlated. To address this concern, they used varieties of $E(z|x)$ as IVs.[9] As criticized in subsequent studies, this strategy is

[8]In Sacerdote (2000), additional information of error structure was used to identify β and γ as we will see in the next subsection. He found γ to be negligible. After this finding, he used $\gamma = 0$ to identify the endogenous effect.

[9]The metropolitan area unemployment rate, median family income, poverty rate, and the percentage of adults who completed college were used as IVs.

dubious because the correlation of u and x (caused by endogenous sorting) implies the correlation of u and $E(z|x)$. Thus $E(z|x)$ is not ideal IVs for $E(y|x)$. Accordingly, their conclusion that peer effects do not exist after controlling endogenous sorting is dubious as well.

Sacerdote (2000) used random assignment of roommates in a college dorm to avoid this endogenous sorting. This natural experimental situation effectively rules out endogenous sorting. Gaviria and Raphael (2000) divided the sample into two sub-samples: families that had moved in previous two years and the families that had not moved. They argued that if endogenous sorting is widespread, estimates of peer effects for families that had recently moved into a new neighborhood should be larger. Their findings were mixed.[10] Although this method does not capture endogenous sorting that had occurred more than two years earlier, the important issue here is whether peer effects are critically different across groups. This is a clever possible strategy when the random assignment of peers is not available.

3.4.3 Identification through variance covariance structure

The identification strategies introduced so far all assume the absence of the contextual effect ($\gamma = 0$). To the best of my knowledge, the only paper that attempts to relax this assumption is Sacerdote (2000). Since there are only two students in a dorm room, the system of interest is

$$y_i = \alpha + \beta y_j + z_j \gamma + z_i \eta + u_i, \tag{3.9}$$

$$y_j = \alpha + \beta y_i + z_i \gamma + z_j \eta + u_j, \tag{3.10}$$

where $Var(u_i) = Var(u_j) = \sigma_u^2$ is assumed and $E(u_i|z_i, z_j, u_j) = E(u_j|z_i, z_j, u_i) = 0$ is assured from the random assignment. Substituting (3.10) into (3.9), the reduced form

$$y_i = \frac{\alpha + \alpha\beta}{1 - \beta^2} + z_j \frac{(1 + \beta)\gamma}{1 - \beta^2} + z_i \frac{(1 + \beta)\eta}{1 - \beta^2} + \frac{u_i + \beta u_j}{1 - \beta^2} \tag{3.11}$$

[10] Different peer effects were found in the two sub-samples for marijuana usage but not in drinking, smoking, church attendance or dropping out of high school.

is obtained. Estimating this equation through OLS, three coefficient estimates are produced. Since there are five parameters $(\alpha, \beta, \gamma, \eta, \sigma_u^2)$, two more estimates are required to recover all of them. The remaining two functions used for identifying the parameters come from the variance and covariance structure of error terms due to the randomness of the roommate assignment. Then the variance and covariance structures are

$$Var(\frac{u_i + \beta u_j}{1-\beta^2}) = \frac{1+\beta^2}{(1-\beta^2)^2}\sigma_u^2 \tag{3.12}$$

and

$$Cov(\frac{u_i + \beta u_j}{1-\beta^2}, \frac{u_j + \beta u_i}{1-\beta^2}) = \frac{2\beta\sigma_u^2}{(1-\beta^2)^2}. \tag{3.13}$$

Using three coefficients estimates of the OLS and the estimates of variance and covariance of residuals, parameters $(\alpha, \beta, \gamma, \eta, \sigma_u^2)$ are recovered.[11] Comparing the two estimates of β obtained through this method and obtained assuming $\gamma = 0$,[12] he found similarity between the two estimates and concluded that the peer effect works through the endogenous effect rather than the contextual effect (i.e., $\gamma = 0$ is not restrictive assumption.) Although this is a path breaking approach, the identification crucially depends on the homoscedasticity assumption embodied in (3.12) and (3.13). It is not clearly *a priori*, however, if all of the students in dormitories share equal variances in the unobservable characteristics. As in the usual discussion, the identification off the assumption of error structure is rather tenuous. Results obtained in this study thus are informative but not definitive. It should be noted, however, that this approach is the best one can take with a data set that contains only observed behaviors.

3.4.4 Identification through dynamic structure

Manski (1993) introduced some studies that exploit the dynamic structure of peer effects transmission. The estimated equation is the dynamic version of (3.2):

$$E_t(y|x,z) = \alpha + \beta E_{t-1}(y|x) + E_{t-1}(z|x)\gamma + z_t\eta + x_t\delta. \tag{3.14}$$

[11] Standard errors of those estimates are calculated through bootstrapping.

[12] Even under assumption of $\gamma = 0$, regression of y_i on y_j and z_i does not render unbiased estimator of α, β, η and σ_u^2 since $E(u_i|y_j, z_i) \neq 0$ since y_j is a function of z_j, u_j and u_i as shown in (3.11) even if $\gamma = 0$. His discussion is not quite correct in this sense.

Since peer effects do not operate contemporaneously, the estimation is free from the "reflection problem" and opens the possibility for estimating peer effects.

Studies of Biddle (1991) and Norton, Lindrooth, and Ennett (1998) fall into this category. Biddle (1991) analyzed peer effects in the demand for personalized license plates using state-level aggregate data. In his study, y_t is current demand of personalized license plate in state x, $E_{t-1}(y|x, z)$ is the demand in the last year, z_t includes state aggregate income and the number of cars in a state. State dummies are included as x_t. He implicitly assumed $\gamma = 0$. He found significant peer effects in the demand.

Norton, Lindrooth, and Ennett (1998) analyzed peer effects in sixth to ninth graders' substance uses. In their study, y_t is sixth to ninth graders' current use of substances, and $E_{t-1}(y|x)$ is average use of substances among students who attended the same primary school. The vector z_t included sets of demographic and regional characteristics. They implicitly assumed $\gamma = 0$. Since peer effects are defined at an earlier schooling level, the estimation of peer effects is the dynamic version. The result of estimation showed that β is in the neighbor of 1.

Although these estimators are immune from Manski (1993)'s criticism, one should realize that identification of β crucially depends on the exclusion of contemporaneous peer effect by assumptions. Once the assumptions break down, Manski (1993)'s criticism again applies to these two studies. It is not clear whether the contemporaneous peer effect can be ruled out in those two studies *a priori*.

3.4.5 Identification through sibling method

Aaronson (1998) attempted to address the heterogeneity bias caused by household heterogeneity such as parents' "willingness" to invest in their children. He estimated the effect of neighborhood quality, measured by poverty rate or average dropout rate, on a teenager's dropping out of high school. His model specifies outcome as

$$y_{ijt} = \alpha + E(y|x)_{tj}\beta + z_{ijt}\eta + c_j + u_{ijt}, \tag{3.15}$$

i, t and j index individual, time, and household, respectively. $E(y|x)_{tj}$ is a regional average and c_j denotes an unobserved household heterogeneity. Absence of the contextual effect was assumed. The sibling method differences out c_j but it also differences out $E(y|x)_{tj}$ if it is time invariant. Thus, the identification of the peer effect, β, crucially depends on the time variance of $E(y|x)_{tj}$ along with the time invariance of household heterogeneity, c_j. To obtain variation in $E(y|x)_{tj}$, he used a sibling sample from households that moved. As Aaronson (1998) noted, however, the residential change and change of family's unobservable components are likely to be correlated,[13] and consequently the time invariance assumption on c_j may be violated. Moreover, the change of x should affect individual behavior only through the change of $E(y|x)$ (i.e., the assumptions $\gamma = 0$ and $E(u|x, z) = 0$ are critical.). Regardless of these restrictions, it is informative that he found significant peer effects even after controlling household heterogeneity, since the bias caused by the household heterogeneity was critical concerns in previous studies.

The sibling method is also employed in this study to identify the endogenous effect; however, time invariance of household heterogeneity is no longer needed by using subjective perceptions of peers' behaviors, since the siblings' perceptions may vary within a household. Accordingly, c_j can be differenced out without differencing out perceptions.

3.4.6 Identification through economic theory

So far, I have surveyed identification strategies that only use observed behaviors as information. On the other hand, there are several notable studies that identify peer effects using prior knowledge suggested by economic theory.

Neumark and Postlewaite (1998) suggested "relative income concern" as a factor to explain the rapid increase of the labor force participation (LFP) rate among U.S. married women. Constructing an economic model of "relative income concern," they actually estimated peer effects on labor force participation among married American women. They used a sister-in-law's LFP as the peers' behavior and regressed a woman's

[13] Negative unobservable shock within a family may make the family move.

LFP on her sister-in-law's LFP. They found significant peer effects on the LFP decision. Moreover, they directly estimated the prediction obtained from their theory. The theory predicts that a woman is more likely to be employed if her husband's income is less than her sister-in-law's husband's income and the sister-in-law is not employed. This is because the woman's household may "win" in the income race due to the woman's additional earnings. On the other side of coin, a woman is less likely to be employed if the woman with the husband whose income is less than the sister-in-law's and her sister-in-law is employed. This is because the household is unlikely to "beat" the sister-in-law's household with the woman's additional earnings. The estimated result of this "best response function" was consistent with theoretical prediction.

Munshi (2000) also avoids spurious findings by using predictions from economic theory. He analyzed the technological diffusion during the Green Revolution in India. He used the technological characteristics that the High Yield Variety (HYV) of rice is more sensitive to unobservable land quality than is the high yield variety of wheat. As a consequence of this technological factor, economic theory predicts stronger peer (social) effects for the diffusion of wheat. This is because, roughly speaking, an agent cannot learn much from his/her neighbor's experience when the success of technology adoption strongly depends on unobserved heterogeneous factors. The data supported this prediction; he found stronger peer effects in the wheat HYV diffusion than in the rice HYV diffusion.

These studies are persuasive because they carefully examined theoretical predictions and did more than regress the individual outcomes on group outcomes. Accordingly, these studies are free from Manski (1993)'s criticism. This strategy, however, can only be applied to the situation in which sharp theoretical predictions are available.

3.5 Estimation

This review of the existing research clearly indicates the limitation of studies that use only observed behavior to identify the endogenous effect. As has been discussed, economic theory can provide precious information for the identification of these effects. In the context of substance usage by teenagers, however, obtaining such a theoretical prediction is difficult since the preferences of teenagers, which are necessary to derive behavioral predictions theoretically, are largely unknown *a priori*. I thus use perceived peer behaviors, which are potentially error ridden, as additional information to identify the endogenous effect. The description of data, the econometric model, and the results of estimations follow.

3.5.1 Data

The data set used in this study is the National Longitudinal Survey Youth 97 GeoCode file. The sample construction is summarized in Table 3-1. I used the set (10) (N=6356) as a sample for the cross-sectional studies, and I applied (almost) school fixed effect estimation and sibling fixed effect estimation to the set (11) (N=6312) and (12) (N=2458) respectively. In Table 3-1, the sample means of outcomes are tabulated. From the tabulation, we can confirm that the sample selection does not drastically change the property of sample in terms of outcomes.

The outcomes are constructed by using questions about substance use in last 30 days. The respondent who smokes/drinks more than or equal to one cigarette/drink is defined as a smoker/drinker; similarly, the respondent who uses marijuana more than or equal to once per month is defined as a marijuana user.

In order to construct the peer variables, respondents were asked about their subjective perception of their peers' behavior by the following questions:

"What percentage of kids (in your grade / in your grade when you were last in school) (smoke/smoked) cigarettes?

(get/got) drunk at least once a month?

(have / ever)used marijuana, inhalants, or other drugs?"

Respondents were allowed to answer the questions with one of the following five categories:

1. almost none (less than 10%)
2. about 25%
3. about half (50%)
4. about 75%
5. almost all (more than 90%).

From these categories, I constructed perceived peers' behaviors in which "almost none" was coded as 0, and "almost all" was coded as 1.

Descriptive statistics of individual substance uses and perceived peer substance uses are tabulated in Table 3-2. An interesting finding is that the respondents systematically overestimate peer behaviors and the degree of overestimation is not negligible. It is worth noting that this measurement error is not a problem if we assume the variable that affects the respondents' behaviors is the perceived peer behaviors rather than the "objective" (for econometricians) peer behaviors.[14]

3.5.2 The model

The substance use by a teenager is specified as

$$y = \alpha + \beta p + E(z|x)\gamma + z\eta + u, \tag{3.16}$$

where y is a binary variable set to one if the individual is a substance user. The variable p is perceived peer behaviors. The vector z contains a set of student, family, school, and

[14]The difference between the subjective measure and the objective measure of the peer behaviors implies that we cannot calculate the social multiplier effect from the size of endogenous effect (β), since we need to know how individuals formed their perceptions. Only with perceived peer behaviors, however, can we confirm the existence of the endogenous effect without assuming absence of the contextual effect (i.e. $\gamma = 0$), as discussed before.

regional characteristics that may affect individual substance use. The variable x is an attribute of the group, which is "schools" in this model. The determination of perceived behavior is specified as

$$p = \theta_1 E(y|x) + z\theta_2 + E(z|x)\theta_3 + v. \tag{3.17}$$

I assume $E(u|x, z) = 0$ and $E(v|x, z) = 0$. Inclusion of several measures of parental involvement in vector z such as participation in PTA meetings and many variables (85 total) that may affect a youth's substance use, makes the assumption $E(u|x, z) = 0$ plausible.

There are still potential sources of omitted variable bias. For example, state anti-drug campaigns to reduce teenager substance use is a possible omitted variable that may affect both a respondent's and his or her peer's substance use ("correlated effect," using Manski (1993)'s terminology). In this situation, the violation of $E(u|x, z) = 0$ is likely to occur through $E(u|x, z) = f(x)$. To reduce this possibility, I included many regional variables in z that characterize the county where the teenager lives (e.g., state cigarettes tax rate, beer tax rates, county-level poverty rate, county-level unemployment rate, the demographic composition of the county, and other characteristics). It is still fair to say, however, that the assumption $E(u|x, z) = 0$ can be violated. Thus, I will later relax this assumption and use fixed effect estimation.

To ensure that the OLS is an unbiased and consistent estimator, I also assume

$$E(u|x, z, v) = 0. \tag{3.18}$$

This means that the error term of the behavioral equation (u) is not correlated with the error term in the equation determining perceptions of peer behaviors (v). Under this assumption, applying OLS (3.16) renders an unbiased and consistent estimator of β, γ and η because

$$E(u|z, p, x) = E(u|x, z, p(E(y|x), z, v)) = E(u|x, z, v) = 0. \tag{3.19}$$

The cell average of z within a school is used instead of $E(z|x)$.[15] Since u is heteroscedastic due to the binary dependent variable, the variance covariance matrix is calculated using the White formula.

Since the respondent's school identification number (ID) is not available in my data set, I create the (almost) school ID by matching the respondent's county ID, school size and student/teacher ratio.[16]

3.5.3 The results

I report the results of the above model in Table 3-3.

For cigarette smoking, the coefficient 0.221 means that a 10 percentage point increase in the subjective perception of the peer smoking probability increases the probability of smoking by 2.2 percentage points. This estimate is statistically significant. For alcohol drinking, the estimated coefficient is 0.311. For marijuana usage, the OLS estimate is 0.229.

The results clearly show the existence and statistical significance of peer effects. When a teenager's perception of the percentage of his/her peers who use a substance increases by 10 percentage points, the probability that he/she will use the substance increases from 2.2 to 3.1 percentage points. Although the difference in identification strategy prohibits me from serious comparison of the estimates, the estimated peer effect is comparable to the estimated effect of Gaviria and Raphael (2000) for smoking and alcohol drinking (0.150 for smoking, 0.106 for alcohol drinking and 0.254 for drug

[15] Although this first step estimation may change the asymptotic distribution of the OLS estimators, it is known that under the null of $H_0 : \gamma = 0$ the asymptotic distribution is not affected.

[16] School size is classified into five categories: 1-299, 300-499, 500-749, 750-999, and 1000+ students. Student/teacher ratio is classified into four categories: less than 14, 14-17, 18-21 and more than 22. The Bureau of Labor Statistics assigns these two variables to each respondent based on the confidential information held by BLS. Thus, when each school in a county is different in either school size or student/teacher ratio, I can identify all of the schools. If all of the schools in a county share both the same school size and student/teacher ratio, I just identify the county. In the worst-case scenario, it is to assume $E(z|x)$ is constant within a county. This mis-matching becomes serious if the variation of $E(z|x)$ is huge within a county. However, the direction of bias in the estimator of γ caused by this measurement error is not clear *a priori*, since the measurement error is mean reverting (to the county mean) and not classical. The contextual effect that operates at the county level is, however, at least captured.

use). The absence of the contextual effect ($\gamma = 0$) is not rejected through an F-test. In summary, the results of the estimation robustly show the existence of peer effects in the *causal* sense. Moreover, due to the usage of perceived peer behavior as the key independent variable, the results show that peer effects work through the endogenous effect. This implies the existence of the "social multiplier."

The causal interpretation critically depends on the assumption $E(u|x, z, v) = 0$. The multitude of variables in z (82 in total), however, makes this assumption realistic.[17]

3.6 The (almost) school fixed effect estimation

Although the previous section made the best effort to assure the assumption $E(u|x, z, v) = 0$ is correct, the school attribute x nonetheless may still contain some information which systematically predicts teenagers' substance use that the regional or school characteristics included in z fail to capture. In other words, there might be regional and school factors that encourage the teenagers' substance use that are not observed. For example, suppose a cigarette shop is located just in front of high school A. Moreover, suppose this "unobservable" makes a student in the high school 50 percentage points more likely to smoke. Then the assumption $E(u|x, z, v) = 0$ is violated, because

$$E(u|x, z, v) = \begin{cases} 0.5, & \text{if } x = A, \\ 0, & \text{Otherwise.} \end{cases} \tag{3.20}$$

This possibility is addressed through school fixed effect estimation, which can be represented in the equation

$$y_{ij} = \beta p_{ij} + z_{ij}\gamma_1 + E(z|x)_j\gamma_2 + a(x)_j + u_{ij}. \tag{3.21}$$

Here i is a subscript for an individual and j is a subscript for a school. The coefficient γ_2 is not identified, since $E(z|x)_j$ is invariant within a school. The random variable $a(x)_j$

[17] If the instrumental variables that are sufficiently correlated with p but not correlated with u exist, we can use Hausman (1978)'s method to test endogeneity of p. In particular, specifying $E(u|x, z, v) = \rho v$, $H_0 : \rho = 0$ can be tested given $E(u|x, z) = 0$. However, finding such IV is prohibitively difficult.

captures the school specific unobservable which affects the teenager's substance usage, such as a cigarette shop at the school gate.

Under the assumptions $E(u|p, z, a, x) = 0$ and $E(a|p, z, x) = 0$, both the random effects estimator and fixed effects estimator are consistent. However, only $E(u|p, z, a) = 0$ needs to be true for the consistency of the fixed effect estimator. This allows for a test of the assumption $E(a|p, z, x) = 0$ using a Hausman test. Since the random effect estimator is not efficient due to heteroscedasticity, I use the robust form of the Hausman test introduced in Wooldridge (2001). Although it is not rigorously justified, the single variable Hausman test roughly tests the null $E(a|p, z, x) = 0$. Under this assumption, the estimator of the coefficient for p is roughly consistent.[18] The results of the random, fixed effect estimation and the Hausman tests appear in Table 3-4. All of the Hausman tests do not reject the null of $E(a|p, z, x) = 0$. Thus I am in favor of using the random effect estimator because of its relatively efficient property. Peer effects for smoking, drinking and marijuana usage are 0.22, 0.31, and 0.23 respectively. These numbers are similar to the OLS results. This is probably due to the fact that the vector z already contains enough information to capture the school "unobservable."

3.7 The household fixed effect estimation using the sibling sample

To reinforce the previous results, I estimate the household fixed effect model using sibling samples. One concern in the previous research (Evans, Oates, and Schwab (1992)) was the endogeneity of peer quality due to omitted household characteristics. Peer quality can be endogenous since parents who are willing to invest in their children send their children to a school with good peers. Parental care can also directly affect a child's behaviors. This problem can be avoided through controlling household unobserved heterogeneity using the household fixed effect estimation.[19]

[18] This discussion is not exactly true as far as p is correlated with the other explanatory variables.

[19] The sibling method, however, does not necessarily solve the endogeneity. Since between household difference of outcomes and perceived peer behaviors are wiped away, the identification solely depends on

I estimate the following model:

$$y_{ij} = \beta p_{ij} + z_{ij}\gamma_1 + E(z|x)_{ij} + c_j + u_{ij} \tag{3.22}$$

where i is a subscript for an individual, j is a subscript for a household, and c is a household unobserved heterogeneity. The same econometric discussion from the previous section applies.

The results of random and fixed effects estimation and the Hausman tests appear in Table 3-5. All of the Hausman tests reject the null of $E(c|p, z, x) = 0$. Thus, the fixed effects estimator is preferred. These results are similar to the previous OLS results that appeared in Table 3-4. Peer effects for smoking, drinking and marijuana usage are 0.14, 0.27, and 0.21 respectively. The fixed effects coefficient estimates are smaller than those obtained from the random effects or OLS estimation due to the positive correlation of the household unobserved heterogeneity and the peer variable. Nevertheless, even after allowing for the correlation of the household heterogeneity and the peer variable through the fixed effect model, the estimated peer effects are practically and statistically significant.

3.8 Peer effects and the demographic groups

Thus far, the existence of peer effects is a robust result. Next, it is interesting to investigate the strength of peer effects within different demographic groups. With knowledge of the group in which the endogenous effects are strong, policy makers can effectively target the policy that is likely to discourage youth substance use within that group, since he/she can expect larger policy effects through the larger "social multiplier".[20] To

within household variation of outcomes and perceptions. If each sibling in a household has unobserved characteristics that determine both substance use and perception of peer behaviors, the sibling estimator is still biased. If this within household unobservable plays a more important role than the between households unobservable, the sibling estimator can be more biased. However, this discussion is unlikely to apply in the context of substance use. See Bound and Solon (1999) and Neumark (1999) for possible biases in the sibling estimator of the return to education.

[20]This discussion assumes, though, that sensitivity to the policy (a part of η) is the same across groups.

estimate the difference in the endogenous effects across groups, I assume the following model in which the strength of peer effects may depend on the different demographic groups:

$$y = \alpha + \beta_1 p + p * z_1 \beta_2 + z\gamma + E(z|x)\eta + u, \tag{3.23}$$

where z_1 is the part of z that defines demographic groups.[21] Since the exogeneity of p was not rejected in the school and household fixed effects estimation, I assume $E(u|p, z, x) = 0$. Under this assumption, OLS is an unbiased estimator.

The results of the regressions appear in Table 3-6. Some of the estimated coefficients on the interaction terms are statistically significant and the effects are not negligible. As for the marijuana usage, females are less likely than males to be affected by their peers. For the other two substances, a gender difference was not found. Fewer peer effects were found among black teenagers. For smoking behavior, peer effects among black teenagers are one-third of that found among white teenagers. The smaller peer effects among black teenagers are statistically different from zero for all substances. Hispanics are also less vulnerable to peer pressure. An expectation is that minority teenagers might not obtain as much utility as non-minority teenagers from imitating each other. Teenagers with both biological parents are less likely to be affected by their peers in their smoking and marijuana uses. As for drinking, the coefficient on the interaction term of the peer variable and "both biological parents" is not statistically significant. The first two results may imply that the teenager who does not have both biological parents present is more likely to depend on his peers to form his behavior. This result is consistent with Steinberg (1987)'s. The result was not obtained in Gaviria and Raphael (2000), probably because the peer variable only interacts with the single parent dummy, not with the race dummies.

[21] I also estimated the endogenous effect using a sub-sample of demographic groups. The results obtained were qualitatively the same as the results obtained in this section.

3.9 Conclusion

The estimation of peer effects on substance usage through perceived peer behaviors shows the existence of significant peer effects. When the perceived peer substance use is doubled, the probability that a teenager will use substances increases by forty to sixty percentage points. Moreover, the endogenous effect is found to be more important than the contextual effect when explaining the peer effects on youth substance use. This finding implies that current peer behaviors, rather than peer backgrounds, determine individual behaviors. Thus, if some exogenous shock reduces a group's substance use, this reduction propagates to other groups of youths through the endogenous effect. Hence, policy makers can expect a "social multiplier" effect in policies that discourage youth substance use.

In my model, the endogenous effect is identified when perceived peer behaviors are exogenous. To assure this exogeneity assumption, I used a rich set of controls consisting of parent, neighborhood and school characteristics. Moreover, the robustness of the results is confirmed through the school and household fixed effect estimations. We also find that the strength of peer effect depends on the demographic group to which a teenager belongs. Peer effect is found to be large among white teenagers and teenagers without both biological parents.

Although this paper finds a robust peer effect, this study does not shed enough light on the mechanism of peer effect itself. Thus this study is still a "reduced form" study of peer effects. More direct research on the mechanism of peer effect is left for future research. Also, peer effects on the several other socioeconomic behaviors such as criminal or sexual activities are the topics for the future research. I hope the robust findings in this study stimulate further investigation in this field.

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Table 1-1: The replication of the Lazear and Moore (1984)'s finding and the risk of self-employed workers.

	(1)	(2)	(3)	(4)	(5)	(6)
Model	OLS	F.E.	OLS	F.E.	OLS	F.E.
Dependent variable	ln wage	ln wage	Residual^2 of (2)	Residual^2 of (2)	Residual^2 of (2)	Residual^2 of (2)
education	0.070	–	–	–	–	–
	(0.003)					
experience	0.063	0.112	–	–	–	–
	(0.005)	(0.008)				
$experience^2/100$	-0.120	-0.187	–	–	–	–
	(0.026)	(0.019)				
tenure	0.052	0.032	–	–	–	–
	(0.004)	(0.003)				
$tenure^2/100$	-0.250	-0.198	–	–	–	–
	(0.029)	(0.020)				
self- employed	0.032	0.086	0.237	0.189	0.201	0.172
	(0.033)	(0.018)	(0.041)	(0.038)	(0.056)	(0.046)
$self \times (educ - \overline{educ})$	-0.007	–	–	–	–	–
	(0.011)					
$self \times (ex - \overline{ex})$	-0.043	-0.043	–	–	–	–
	(0.020)	(0.012)				
$self \times (ex^2 - \overline{ex^2})/100$	0.193	0.146	–	–	–	–
	(0.088)	(0.049)				
$self \times (ten - \overline{ten})$	-0.054	-0.031	–	–	–	–
	(0.016)	(0.009)				
$self \times (ten^2 - \overline{ten^2})/100$	0.243	0.228	–	–	–	–
	(0.100)	(0.057)				
$(self - \overline{self})^2$	–	–	–	–	0.133	0.059
					(0.092)	(0.090)
Constant	5.566	–	0.147	–	0.145	–
	(0.058)		(0.009)		(0.088)	
Observations	23887	23887	23887	23887	23887	23887
Number of individuals	–	2715	–	2715	–	2715
R^2	0.31	–	–	–	–	–
Wage of SE – Wage of SW						
0 year experience and	0.343	0.357				
0 year tenure	(0.107)	(0.061)				
5 years experience and	-0.034	0.080				
5 year tenure	(0.059)	(0.032)				
10 years experience and	-0.192	-0.011				
10 year tenure	(0.062)	(0.035)				

Notes:

1. Standard errors are in parenthesis for coefficient estimates. For OLS estimates, standard errors are corrected for the panel clustering.
2. Dependent variable in the each regression (3), (4), (5) and (6) is the squared idiosyncratic residual of regression (2).
3. Year dummies are included but coefficients are not reported.
4. Wage of SE - Wage of SW is evaluated at the sample mean of education that is 13.107.

Table 1-2: School Enrollment by Sectors (1988-1998)

	Salary and Wage	Self Employed	Total
Enrollment Rate	9.01	5.60	8.67
N	16021	1804	17825

Notes:

1. The workers who were enrolled in school at all between last interview date and current interview date are classified as "enrolled." This does not necessarily imply current enrollment.
2. Only observations after year 1988 are included in the sample. Youngest respondents are 24 in 1988.

Table 1-3: Linear Probability Model of School Enrollment
Dependent Variable: Enrolled in School (Yes=1, No=0)

	(1)	(2)
Mean of Dependent Variable	0.087	0.087
Method of Estimation	OLS	F.E.
Self-Employed	-0.024	-0.019
	(0.008)	(0.009)
Education	0.026	–
	(0.002)	
Experience	-0.015	-0.040
	(0.004)	(0.006)
Experience^2	0.045	0.081
	(0.015)	(0.013)
Tenure	-0.012	-0.007
	(0.002)	(0.002)
Tenure^2	0.055	0.039
	(0.011)	(0.012)
Constant	-0.138	0.508
	(0.030)	(0.080)
Observations	17825	17825
R-squared	0.07	0.02
Number of ID	–	2634

Note: The same note applies as Table 2. Standard errors are in parenthesis for coefficient estimates. For OLS estimates, standard errors are corrected for the panel clustering.

Table 1-4: Training Participation by Type of Training and Cost Bearing (1988-1998)

Panel A: Training Participation by Type of Trainings

	Salary and Wage	Self-Employed	Total
Not Participate in Training	81.09	90.74	82.06
On-the-job Training	11.67	3.61	10.85
Apprenticeship Program	0.75	0.28	0.70
Formal Company Training Run by Employer or Military Training	7.35	1.83	6.79
Seminars or Training Programs at Work Not Run by Employer	3.57	1.50	3.36
Off-the-job Training	6.20	5.00	6.07
Business School	0.29	0.33	0.29
Vocational or Technical Institute	1.45	0.67	1.38
Correspondence Course	0.52	0.28	0.49
Seminars or Training Programs outside of Work	3.71	3.55	3.69
Vocational Rehabilitation Center	0.14	0.11	0.13
Government Training Program	0.09	0.06	0.09
Other	1.05	0.67	1.01
N	16014	1804	17818

Panel B: Training Participation by Type of Cost Bearing

	Salary and Wage	Self-Employed	Total
Not Participate in Training	81.09	90.74	82.06
Training Cost Paid by Self or Family	1.57	3.88	1.81
Employer	15.87	3.60	14.63
Job Training Program Act	0.14	0.11	0.14
Trade Adjustment Act	0.02	0.06	0.02
Job Corps Program	0.01	0.00	0.01
Work Incentive Program	0.01	0.00	0.01
Veteran's Administration	0.02	0.06	0.03
Vocational Rehabilitation	0.09	0.00	0.08
Other	1.17	1.55	1.21
N	16014	1804	17818

Notes:

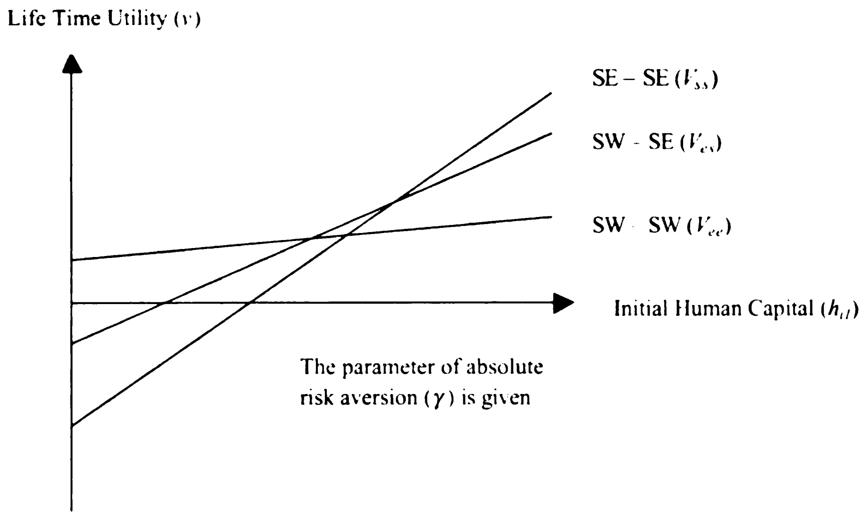
1. The results are based on most recent participating training program that starts between the last interview date and the current interview date.
2. Among types of training, "Business School," "Vocational or Technical Institute," "Correspondence Course," "Seminars or Training Programs outside of Work" and "Vocational Rehabilitation Center" are classified as off-the-job training.
3. Trainings paid by "Self or Family" and government programs are classified as "own cost training."

Table 1-5: Linear Probability Models of Training Participation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	SE and SW		SE and SW			SW Only	
Dep. Var.	Training		Off-JT		Training	Off-JT	Own/Gov. Paid
Mean	0.179		0.061		0.179	0.061	0.033
Method of Estimation	OLS	F.E.	OLS	F.E.	OLS	OLS	OLS
SE	-0.097	-0.050	-0.012	-0.010	–	–	–
	(0.009)	(0.013)	(0.006)	(0.009)			
Future Self	–	–	–	–	-0.057	-0.001	0.014
					(0.012)	(0.008)	(0.006)
Education	0.024	–	0.008	–	0.024	0.006	0.000
	(0.002)		(0.001)		(0.002)	(0.001)	(0.001)
Experience	-0.003	0.000	-0.003	-0.005	-0.003	-0.005	-0.006
	(0.004)	(0.009)	(0.003)	(0.006)	(0.005)	(0.003)	(0.003)
Experience^2	0.023	0.010	0.020	0.016	0.020	0.025	0.019
	(0.018)	(0.019)	(0.011)	(0.013)	(0.025)	(0.016)	(0.012)
Tenure	0.006	-0.006	-0.001	-0.002	0.008	-0.001	-0.005
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)
Tenure^2	-0.038	0.025	0.009	0.022	-0.049	0.014	0.022
	(0.018)	(0.017)	(0.012)	(0.012)	(0.025)	(0.016)	(0.008)
Constant	-0.148	0.195	-0.035	0.117	-0.103	0.000	0.095
	(0.032)	(0.120)	(0.018)	(0.079)	(0.037)	(0.021)	(0.017)
Observations	17818	17818	17818	17818	13671	13671	13671
R-squared	0.04	0.01	0.01	0.00	0.03	0.01	0.01
Number of ID	–	2634	–	2634	–	–	–

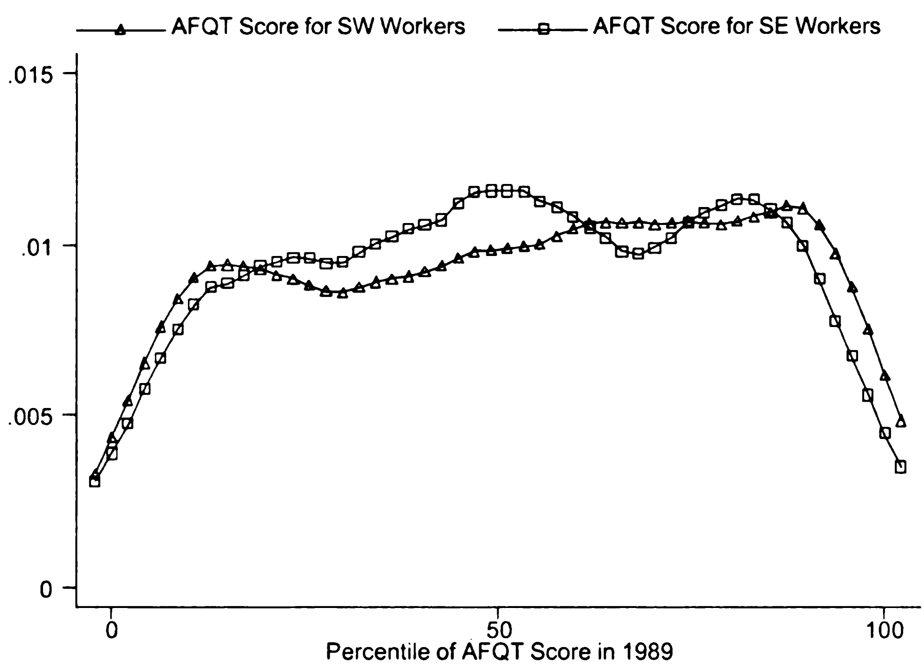
Note: The same note applies as Table 2. Standard errors are in parenthesis for coefficient estimates. For OLS estimates, standard errors are corrected for the panel clustering.

Figure 1-1: Life Time Utility of Each Career Path and Initial Human Capital



Note: SE: Self-Employed workers; SW: Salary and Wage workers.

Figure 1-2: Distribution of test scores among SE and SW workers



Note: Bandwidth = 6 and Epanechnikov kernel was used to estimate the kernel density. The distribution of percentile ranges from –5 to 105 because of the bandwidth = 6, actual distribution of the percentile of AFQT89 ranges from 1 to 99. Workers who were both SE and SW over their careers contribute to both populations on a career-weighted average.

Table 2-1: Sample Construction

	Total	Salary Wage workers	Self-employed workers
Original NLSY79 1985-1998	152232		
White	90120		
Male	45480		
Employed + out of school	24756		
Work in private, government and self-employed	24580		
Valid answer for job satisfaction: Sample (1)	24533	22095	2438
Employed + out of school for two consecutive interviews	19893		
Valid class + tenure variables	19402		
Work in private, government and self-employed for two consecutive interviews	19298		
Valid answer for job satisfaction: Sample (2)	19222	17265	1957
Sample (2) + lagged demographic variables are available: Sample (3)	13889	12512	1377
Sample (1) + valid covariate + more than 2 years of observation: Sample (4)	20454	18585	1869
Hourly wage/earnings are between 1 percentile and 99 percentile: Sample (5)	20065	18328	1737

Note:
Tenure variable is used to identify job change. Sample (1) is used in the analysis of Table 2-3. Sample (2) is used in the analysis of Table 2-4. Sample (3) is used in regression analysis.

Table 2-2: OLS Regression Coefficients
Dependent variable: log hourly wage
Sample: White Male (Sample (4))

	(1)	(2)
	OLS	Fixed Effects
Self-employment	-0.011	0.022
	(0.030)	(0.016)
Married-Spouse present	0.093	0.056
	(0.014)	(0.010)
Education	0.078	-
	(0.003)	
Experience	0.047	0.109
	(0.006)	(0.010)
Experience^2 / 100	-0.068	-0.115
	(0.028)	(0.021)
Tenure	0.046	0.029
	(0.004)	(0.003)
Tenure^2 / 100	-0.223	-0.186
	(0.028)	(0.021)
Self-employment × Married - Spouse Present	-0.059	-0.000
	(0.061)	(0.028)
Self-employment × Education	-0.008	-
	(0.012)	
Self-employment × Experience	-0.020	-0.024
	(0.023)	(0.013)
Self-employment × Experience^2 / 100	0.115	0.080
	(0.095)	(0.053)
Self-employment × Tenure	-0.050	-0.027
	(0.016)	(0.009)
Self-employment × Tenure^2 / 100	0.221	0.194
	(0.102)	(0.058)
Constant	5.162	5.923
	(0.044)	(0.044)
Observations	20454	20454
R-squared	0.30	0.26
Number of individuals	2661	2661
Wage of Self-Employed – Wage of Wage and Salaried Workers		
No Experience and No Tenure	0.184	0.209
	(0.128)	(0.071)
5 Year Experience and 5 Year Tenure	-0.084	0.027
	(0.064)	(0.036)
10 Year Experience and 5 Year Tenure	-0.184	-0.018
	(0.064)	(0.037)

Standard errors robust against panel clustering are in parentheses for OLS estimates. Standard errors are in parenthesis for F.E. estimates.

Table 2-3: Job Satisfaction among Workers
Panel A Job satisfaction among salary/wage workers
Sample: White Male (Sample (1))

year	Like very much Row %	Like fairly well Row %	Dislike somewhat Row %	Dislike very much Row %	Total observation
85	45.97	43.27	8.65	2.11	1849
86	43.25	48.13	6.13	2.49	1926
87	41.95	50.56	5.97	1.52	2043
88	41.28	48.82	8.20	1.70	2122
89	43.59	46.89	7.43	2.09	2154
90	41.58	49.84	6.23	2.35	2167
91	43.17	47.58	7.41	1.84	1633
92	43.00	48.49	6.51	1.99	1658
93	42.19	48.85	7.69	1.27	1652
94	41.51	50.60	6.39	1.51	1660
96	43.11	48.93	6.55	1.41	1633
98	46.12	46.62	5.32	1.94	1598
Total	43.00	48.24	6.89	1.87	22095

Panel B: Job Satisfaction among Self-Employed Workers

year	Like very much Row %	Like fairly well Row %	Dislike somewhat Row %	Dislike very much Row %	Total observation
85	72.61	22.29	3.18	1.91	157
86	63.07	31.25	1.70	3.98	176
87	59.90	36.04	2.54	1.52	197
88	64.71	31.22	3.17	0.90	221
89	64.38	33.48	1.72	0.43	233
90	65.07	31.00	3.06	0.87	229
91	70.05	26.40	2.54	1.02	197
92	63.26	33.95	2.33	0.47	215
93	63.59	33.98	1.94	0.49	206
94	62.56	33.33	3.08	1.03	195
96	74.52	22.60	2.40	0.48	208
98	65.69	29.41	3.92	0.98	204
Total	65.67	30.60	2.63	1.11	2438

Table 2-4: Probability to Change Job by the next Interview
Sample: Sample (3)

Job satisfaction in the previous interview	Salaried and Wage Worker	Self-Employed Workers	Mean
Like very much	0.148	0.108	0.143
Like fairly well	0.177	0.207	0.179
Dislike somewhat	0.256	0.383	0.263
Dislike very much	0.388	0.266	0.379
Total	0.173	0.153	0.171
N	12512	1377	13889

Note:
Sample is constructed to be consistent with the sample used for the job change regression.

Table 2-5: Job Change Probit Model
Dependent variable: Job Change between *t* and *t-1*(Yes=1; No=0)
Sample: Sample (3)

	(1)	(2)
Lagged job satisfaction: Dislike very much	0.764	0.734
	(0.098)	(0.099)
Lagged job satisfaction: Dislike somewhat	0.434	0.432
	(0.051)	(0.052)
Lagged job satisfaction: Like somewhat	0.149	0.145
	(0.029)	(0.030)
Self Employment	-0.013	0.006
	(0.062)	(0.064)
Self Employment × Dislike very much	-0.627	-0.567
	(0.308)	(0.291)
Self Employment × Dislike somewhat	-0.123	-0.103
	(0.284)	(0.285)
Self Employment × Like somewhat	0.135	0.130
	(0.099)	(0.102)
Lagged education	-0.017	-0.005
	(0.005)	(0.006)
Lagged experience	-0.012	-0.005
	(0.004)	(0.004)
Lagged tenure	-0.046	-0.047
	(0.004)	(0.004)
Lagged log wage		-0.135
		(0.026)
Constant	-0.545	0.164
	(0.080)	(0.166)
Log Likelihood	-6163	-5979
Pseudo R^2	0.029	0.033
% Correctly Predicted	82.92	81.78
Observations	13889	13592

Marginal effects of Probit model is presented.
Robust standard errors against panel clustering are in parentheses.
Lagged job satisfaction: like very much is the omitted category.

Table 2-6: Transition of Job Satisfaction Associated with Job Change (Percentage)
(SE: Self-Employment Job, SW: Salary and Wage Job)
Sample: White Male (Sample (2))

	Job Satisfaction in Previous Year			
	Like Very Much	Like Somewhat	Dislike Fairly Well	Dislike Very Much
Job Satisfaction in Current Year				
SW in previous year				
Panel A: Job Stayers				
(salary/wage-salary/wage) N=13910				
Like Very Much	30.17	10.34	0.96	0.19
Like Somewhat	13.11	33.26	2.95	0.52
Dislike Fairly Well	1.03	3.79	1.62	0.29
Dislike Very Much	0.31	0.74	0.45	0.27
Panel B: Job Stayers				
(SE-SE) N=1327				
Like Very Much	54.56	9.87	0.38	0.15
Like Somewhat	13.49	17.71	0.75	0.30
Dislike Fairly Well	0.53	0.75	0.60	0.15
Dislike Very Much	0.08	0.30	0.23	0.15
Panel C: Job Changers				
(salary/wage-salary/wage) N=2838				
Like Very Much	21.71	21.04	3.84	1.41
Like Somewhat	12.37	25.55	5.25	1.27
Dislike Fairly Well	1.30	2.85	1.30	0.42
Dislike Very Much	0.42	0.81	0.25	0.21
Panel D: SE in previous year				
Job Changer				
(SE-SE) N=41				
Like Very Much	51.22	12.20	2.44	0.00
Like Somewhat	4.88	24.39	2.44	0.00
Dislike Fairly Well	0.00	0.00	0.00	2.44
Dislike Very Much	-	-	-	-
Panel E: Job Changer				
(wage/salary-SE) N=589				
Like Very Much	40.41	23.09	3.23	0.85
Like Somewhat	7.13	17.15	2.89	0.68
Dislike Fairly Well	1.19	1.87	0.51	0.17
Dislike Very Much	0.17	0.51	0.17	0.00
Panel F: Job Changer				
(SE-salary/wage) N=517				
Like Very Much	39.26	12.19	1.74	0.39
Like Somewhat	18.76	20.50	0.58	0.58
Dislike Fairly Well	2.32	1.35	0.39	0.19
Dislike Very Much	0.97	0.77	0.00	0.00

Table 2-7: The Results of Ordered Probit Estimation
Dependent variable: "Like very much"=4, "like somewhat"=3, "dislike somewhat"=2, "dislike very much =1"
Sample: Sample (5)

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled Ordered Probit	Pooled Ordered Probit	"Fixed Effect" Ordered Probit	"Fixed Effect" Ordered Probit with Feedback	"Fixed Effect" Ordered Probit with Feedback	"Fixed Effect" Ordered Probit with Feedback
Self Employed	0.486	0.489	0.416	0.431	0.431	0.428
	(0.051)	(0.051)	(0.047)	(0.054)	(0.054)	(0.054)
Log wage	0.248	0.232	0.341	0.315	0.315	0.315
	(0.024)	(0.031)	(0.033)	(0.036)	(0.036)	(0.036)
Married		0.044	-0.067	-0.071	-0.071	-0.071
		(0.026)	(0.026)	(0.029)	(0.029)	(0.029)
Education		0.023	0.042	0.039	0.039	0.039
		(0.006)	(0.030)	(0.038)	(0.038)	(0.038)
Experience		0.014	0.001	0.004	0.004	0.004
		(0.005)	(0.009)	(0.011)	(0.011)	(0.011)
Mean(self employed)			0.129	0.143	0.156	0.157
			(0.086)	(0.096)	(0.099)	(0.102)
Mean(log wage)			-0.171	-0.127	-0.127	-0.127
			(0.049)	(0.052)	(0.052)	(0.052)
Mean (married)			0.184	0.185	0.185	0.185
			(0.047)	(0.050)	(0.050)	(0.050)
Mean(education)			-0.016	-0.015	-0.014	-0.015
			(0.031)	(0.039)	(0.039)	(0.039)
Mean(experience)			0.014	0.010	0.010	0.010
			(0.009)	(0.011)	(0.011)	(0.011)
Feedback takes place						
Within 1 year				-0.033		
				(0.046)		
Within 2 years					-0.042	
					(0.046)	
Within 3 years						-0.032
						(0.047)
Year dummies?	Yes	Yes	Yes	Yes	Yes	Yes
3rd Cut Point (μ_3)	-0.377	-0.238	-0.533	-0.478	-0.481	-0.480
	(0.165)	(0.188)	(0.241)	(0.258)	(0.258)	(0.258)
2nd Cut Point (μ_2)	0.360	0.501	0.208	0.282	0.279	0.280
	(0.162)	(0.185)	(0.238)	(0.256)	(0.256)	(0.256)
1st Cut Point (μ_1)	1.891	2.038	1.747	1.823	1.820	1.821
	(0.164)	(0.188)	(0.240)	(0.258)	(0.258)	(0.258)
Mean of predicted latent variable (u)	1.757	1.903	1.613	1.688	1.685	1.686
Monetary Value of Self-Employment status	7.104 (2.596)	8.182 (4.277)	3.387 (0.697)	3.930 (1.045)	3.928 (1.125)	3.893 (1.095)
Observations	20065	20065	20065	17344	17344	17344
Log Likelihood	-19159	-19094	-19066	-16460	-16460	-16460

Note: Panel clustering robust standard errors are in parenthesis for pooled ordered probit estimates.
Standard errors are in parenthesis for "Fixed Effects" effect ordered probit estimates. Married dummy is one if married and spouse present, zero otherwise. Monetary value of self-employment status is calculated by Exp[(coefficient for self-employment)/(coefficient for log wage)]. Standard error for this value is calculated through bootstrapping of 500 repetitions.

Table 3-1: Sample Construction

		N	Average incidence (Non weighted)		
			Smoking	Drinking	Marijuana use
(1)	Whole sample	8984	0.162	0.185	0.086
(2)	All outcomes are available	8940	0.161	0.185	0.085
(3)	Demographic variables are available	8851	0.161	0.185	0.086
(4)	Relationships with parent are available	8833	0.161	0.185	0.086
(5)	All peer variables are available	8518	0.165	0.190	0.088
(6)	School characteristics are available	7498	0.166	0.192	0.091
(7)	Grade in school is available	7495	0.166	0.192	0.091
(8)	Parent's HGC available	7491	0.166	0.192	0.091
(9)	Variables from parent questionnaire are available	6615	0.168	0.193	0.092
(10)	Proxy variables are available* (Basic analysis sample)	6356	0.168	0.195	0.092
(11)	Within school duplication occurs** (School fixed effect analysis sample)	6312	0.167	0.196	0.092
(12)	Siblings data are available*** (Sibling fixed effect analysis sample)	2458	0.170	0.192	0.093

Note:
*Proxy variables for school quality (If experience threat, if something stolen in school, Feel safe in school.) and neighborhood quality (if any gang in neighborhood).
**Since school identification number is not available, quasi-school id, which is made out of county dummy, school size, and student-teacher ratio are used as quasi-school id. Bureau of labor statistics assigns last two variables based on the school id number.
***Siblings are determined by the identical household id.

Table 3-2: Descriptive Statistics of Substance Use and Subjective Measure of Peer's Behavior by Grade

Grade	Smoke last 30 days	Peer who smoke (Subjective)	Drunk last 30 days	Peer who get drunk (Subjective)	Use marijuana last 30 days	Peer who use illegal drug (Subjective)	Number of Observation
4	0	0	0	0	0	0	2
5	0.044	0.118	0.041	0.077	0	0.068	37
	(0.043)	(0.055)	(0.033)	(0.039)		(0.038)	
6	0.058	0.147	0.039	0.037	0.018	0.084	426
	(0.013)	(0.013)	(0.011)	(0.007)	(0.007)	(0.010)	
7	0.097	0.273	0.084	0.111	0.036	0.174	1294
	(0.009)	(0.009)	(0.009)	(0.007)	(0.006)	(0.008)	
8	0.153	0.375	0.146	0.202	0.067	0.257	1319
	(0.011)	(0.009)	(0.011)	(0.008)	(0.008)	(0.009)	
9	0.238	0.529	0.269	0.389	0.145	0.426	1416
	(0.013)	(0.008)	(0.013)	(0.009)	(0.011)	(0.010)	
10	0.260	0.553	0.329	0.481	0.142	0.476	1204
	(0.014)	(0.008)	(0.015)	(0.009)	(0.011)	(0.010)	
11	0.260	0.553	0.329	0.481	0.154	0.474	624
	(0.014)	(0.008)	(0.015)	(0.009)	(0.016)	(0.010)	
12	0.291	0.555	0.371	0.513	0.154	0.487	34
	(0.021)	(0.011)	(0.022)	(0.012)	(0.016)	(0.060)	
Total	0.190	0.427	0.214	0.303	0.099	0.333	6356
	(0.006)	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)	

Note:

1. All statistics are calculated using sampling weight.
2. Standard errors of mean are in parenthesis.

Table 3-3: OLS Estimates of Incidence of Substance Use

	(1)	(2)	(3)
Dependent variable	Incidence of cigarettes smoking in last 30 days	Incidence of alcohol drinking in last 30 days	Incidence of marijuana use in last 30 days
Method of estimation	OLS	OLS	OLS
Peer (Fraction)			
Peer smoke	0.218		
	(0.017)		
Peer drunk		0.309	
		(0.020)	
Peer illegal drug			0.228
			(0.015)
z (Other control variables)	Yes	Yes	Yes
E[z |x] (Contextual Effect)	Yes	Yes	Yes
F-statistics for Contextual effect	1.04	1.01	1.16
	(0.379)	(0.447)	(0.163)
R^2	0.145	0.158	0.128
Sample size	6356	6356	6356

Note:

1. The vector z contains following variables:

z (Independent Variables): Dummies if respondent lives with mother, father, biological mother, biological father, foster mother or foster father. Female dummy, age, black dummy, other minority dummy, Hispanic dummy, school grade dummies (grade 5 – grade 12), [Middle/junior high] school and high school dummies, catholic school dummy, private school dummy, student/teacher ratio category dummies (3 categories), School size category dummies (3 categories), Census regional dummies, urban dummy and proxy variables for unobserved school characteristics (If experience thread, if something stolen in school, Feel safe in school.), parents back ground variables (parent born in U.S., parent speak a language other than English in home, parent was with both biological parents at age of 14), last year's household income category dummies (less than $20,000, $20,001-$40,000, $40,001-$60,000, $60,001-$80,000, more than $80,001, and household income not available.), household size, number of household member less than age 18 and less than 6, proxy variables for parent's involvement in education (Often or sometimes participate in PTA activity, often or sometimes volunteer in school education) dummies for mother's education and father's education, dummy if any gang in neighborhood, county level variables (Share of white population, black population, Indian population, Hispanic population, share of population under 5 years old, 5-17 years old, 18-20 years old, 21-24 years old, 25-34 years old, 35-44 years old, 45-54 years old, 55-64 years old, 65-74 years old and 75+ years old, share of male in population). State tax rates (cigarettes tax and beer tax). There are 85 variables in total, counting each dummy of categorical variable as a variable.

2. White (heteroscedasticity-robust) standard errors are in parenthesis.

3. All of the test statistics are robust against heteroscedasticity.

Table 3-4: Incidence of Substance Use using within School Duplication Data
(Almost school random & fixed effect estimation.)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Incidence of cigarettes smoking in last 30 days		Incidence of alcohol drinking in last 30 days		Incidence of marijuana use in last 30 days	
Method of estimation	Random-Effect	Fixed-Effect	Random-Effect	Fixed-Effect	Random-Effect	Fixed-Effect
Peer (Fraction)						
Peer smoke	0.218	0.218				
	(0.018)	(0.018)				
Peer drunk			0.310	0.305		
			(0.019)	(0.021)		
Peer drug					0.228	0.221
					(0.016)	(0.016)
z (Other control variables)	Yes	Yes	Yes	Yes	Yes	Yes
Hausman Test F (35, 1201)		1.42		1.20		1.68
		(0.014)		(0.124)		(0.000)
Single variable Hausman test t-statistics		0.680		0.740		-0.625
Sample size	6312	6312	6312	6312	6312	6312

Note:
1. School id is not available in data, so the (almost) school id is created out of county id, school size, and student-teacher ratio. Surveyor assigns last two variables based on confidential school id number.
2. Same control variables as in Table 3-4 were included. Some of the variables that do not vary within school dropped in fixed effect.
3. Heteroscedasticity robust standard errors are in parenthesis for estimated coefficient. For test statistics, p-values are in parenthesis. All the tests are robust against heteroscedasticity.

Table 3-5: Incidence of Substance Use using Sibling Data
(Household random & fixed effect estimation.)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Incidence of cigarettes smoking in last 30 days		Incidence of alcohol drinking in last 30 days		Incidence of marijuana use in last 30 days	
Method of estimation	Random-Effect	Fixed-Effect	Random-Effect	Fixed-Effect	Random-Effect	Fixed-Effect
Peer (Fraction)						
Peer smoke	0.207 (0.029)	0.122 (0.040)				
Peer drunk			0.326 (0.033)	0.247 (0.044)		
Peer illegal drug					0.245 (0.025)	0.196 (0.034)
z (Other control variables)	Yes	Yes	Yes	Yes	Yes	Yes
E[z |x] (Contextual Effect)	Yes	Yes	Yes	Yes	Yes	Yes
Hausman Test F (35, 1201)		1.74 (0.000)		1.69 (0.000)		1.21 (0.096)
Single variable Hausman test t-statistics		-3.830		-2.899		-2.944
Sample size	2458	2458	2458	2458	2458	2458

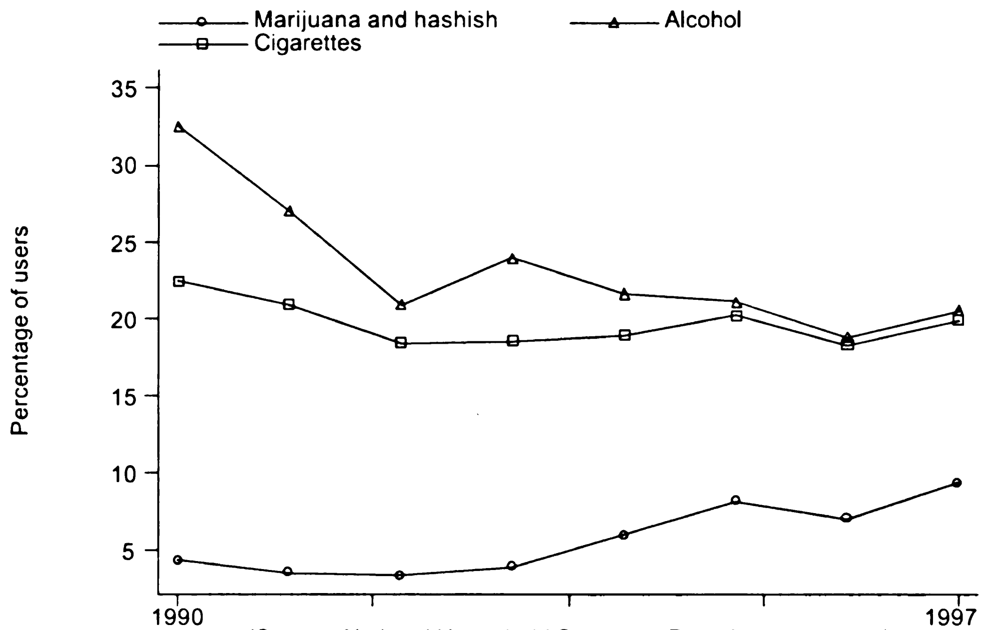
Note:
1. The same control variables as in Table 3-4 were included. Some of the variables that do not vary within household dropped in fixed effect.
2. Heteroscedasticity robust standard errors are in parenthesis for estimated coefficient. For test statistics, p-values are in parenthesis. All the tests are robust against heteroscedasticity.

Table 3-6: OLS Estimates of Incidence of Substance Use

	(1)	(2)	(3)
Dependent variable	Incidence of cigarettes smoking in last 30 days	Incidence of alcohol drinking in last 30 days	Incidence of marijuana use in last 30 days
	OLS	OLS	OLS
Peer			
Peer's substance usage (portion)	0.417	0.440	0.352
	(0.034)	(0.038)	(0.030)
Female × peer's usage	-0.014	-0.050	-0.059
	(0.028)	(0.033)	(0.026)
Black × peer's usage	-0.312	-0.236	-0.175
	(0.032)	(0.038)	(0.029)
Hispanic × peer's usage	-0.128	-0.060	-0.071
	(0.039)	(0.044)	(0.034)
Both biological parents	-0.122	-0.027	-0.047
× peer's usage	(0.029)	(0.033)	(0.027)
z (Other control variables)	Yes	Yes	Yes
R^2	0.143	0.150	0.121
Sample size	6356	6356	6356

Note:
The same note as Table 3-4 applies.

Figure 3-1: Youth Substance Use, Age 12-17, Current Users



(Source: National Household Survey on Drug Abuse, annual.)