The Relativity of Subjective Well-being and the Reference Group

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This paper attempts to test the hypothesis that life satisfaction is dependent not only on absolute income but also on comparison income, i.e. the performance of others. Using a South Korean panel dataset, we show that the negative impact of an increase in comparison income on people's life satisfaction is significant, although it does not outweigh that of absolute income in size. In the case of employees, we find that the average wage rate rise in the same or similar occupation negatively affects their job satisfaction. In addition, the psychic costs of various life events such as unemployment and divorce are estimated. Our calculation suggests that the cost of separation is a lot higher than that of divorce, unemployment, or even widowhood and that the current level of alimony actually paid to divorced women in Korea is too low for their psychological pain to be fully compensated for.

I. Introduction

Individual happiness and well-being have long been a popular research subject for psychologists and sociologists; however, economists have largely ignored such topics for their subjective nature. It was only since the publication of a series of articles in 1997 that happiness research has begun to receive some attention from the economists worldwide.[2)] Despite its short history, a small number of happiness-related economic research have so far found that relative income as well as absolute income matters for job satisfaction (Clark and Oswald 1996), macroeconomic factors such as general unemployment and inflation rates affect individual happiness (Di Tella, MacCulloch, and Oswald 2001), and non-pecuniary costs of unemployment outweigh its pecuniary costs (Clark and Oswald 1994).

Easterlin's (1974) essay is thought to be one of the first economic studies on happiness ever

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2)These ground-breaking articles include Frank (1997), Ng (1997), and Oswald (1997).

published. In his seminal paper, Easterlin studies changes in average happiness over time in the U.S. and finds that a dramatic rise in the GDP per capita did not bring about a comparable increase in the level of individual happiness. He goes on to conclude, based on his time-series data, that economic growth in fact did little to increase people's happiness. Moreover, Easterlin (2001) finds that although there is a significant positive correlation between income and happiness in the cross-sectional data, the same relationship disappears when the life-cycle or time-series data are used instead. This discrepancy between the cross-sectional and time-series evidence is thus called the "Easterlin Paradox".

One reason for the existence of the Easterlin Paradox may be that individuals' happiness depends not only on their own performance, but also on the performance of others. For example, if a rise in one's absolute income is accompanied by everyone else's, he or she may not feel happier due to a comparison effect. Individual happiness may even fall if comparison income rises more than absolute income does. Thus, what this hypothesis suggests is that the rise in income inequality, with a widening gap between the few rich and the numerous poor, can result in a sharp decline in the average happiness index. If relative income, rather than absolute income, is a stronger determinant of individual wellbeing, then the government policy to promote economic growth without caring about the issue of unequal income distribution will need to be reconsidered. Happiness research, in this regard, can be used as an important tool to deliver important macroeconomic policy recommendations.

Some evidence supporting the relative income hypothesis, originally set out by James Duesenberry, is documented in a small number of recent empirical research. For example, Clark and Oswald (1996) test a relative deprivation theory utilizing the job satisfaction data of 5,195 British employees in the BHPS dataset and conclude that the negative effect of comparison income on job satisfaction outweighs the positive effect of absolute income in magnitude. In addition, Brown *et al.* (2003) find that wage satisfaction is partly affected by pure "rank" within the comparison group, as well as by both absolute and relative income measures. The effect of relative income on individual happiness is also well-documented in an extensive study of the U.S. and U.K. time-series data by Blanchflower and Oswald (2004) - the average state income per capita variable has some explanatory power on individual happiness, even when the real family income is controlled for.

Due to data limitation, however, most economic research on happiness have used cross-sectional or non-longitudinal time-series data. Although there are a few exceptions to this, e.g.

Winkelmann and Winkelmann (1998), Hamermesh (2001), and Ferrer-i-Carbonell and Frijters (2004), it cannot be denied that estimations using cross sectional data have dominated the previous research. Needless to say, the use of cross-sectional data can give rise to potential biases in the estimated parameters of relevant explanatory variables. Once source of bias may come from the fact that responses to the subjective wellbeing questions are not interpersonally comparable, due to different characters of respondents or individual heterogeneity. For example, how can we be sure that one person with a happiness rating of four is truly happier than another with three? Differences in personality and psychological traits, thus, are likely to cause an endogeneity or omitted variable bias; one way to eliminate the endogeneity bias arising from the presence of individual fixed effects is to use the longitudinal or panel data that follow the same people over time.

In this paper we will use the Korean Labor and Income Panel Study (KLIPS) to investigate the determinants of subjective wellbeing, utilizing the responses to a set of life and job satisfaction questions. KLIPS is a longitudinal survey of a random sample of Korean households that began in 1998. KLIPS provides various data on the respondents' personal and economic backgrounds, as well as their subjective responses to the questions about life and job satisfaction levels. Exploiting its longitudinal nature, we will make both pooled- and fixed-effects estimations to see if the presence of individual heterogeneity would lead us to make wrong inferences or not. Additionally, non-pecuniary costs of unemployment and several other life events for individuals in Korea will be calculated using the estimated parameters. Furthermore, we will test the relative income hypothesis and find out if relative income matters more for individual happiness than absolute income. The richness of the KLIPS data will allow us to make use of both life-satisfaction and job-satisfaction variables at the individual level. This means that we will be able to double-test the relative income hypothesis once using the family income variable, and then using the individual wage variable.

Another major contribution of our research will be in finding the strongest reference group that individuals compare themselves against, as well as in confirming the relative income effect. Previous economic research has not clearly addressed the issue of "who is in the reference group". The reference group for comparison we can immediately think of is the same age group, same regional group, or the same educational group. As for workers, it can also be the same occupational group. All of these different reference groups might be relevant, but we will attempt to find one group that individuals compare themselves the most with.

This paper is organised as follows. First, in the next section, we will empirically investigate the significant determinants of individual life satisfaction, utilizing the KLIPS data. Following the pooled-OLS and ordered probit estimations, the fixed-effect (within) estimation will be done in order to control for individual heterogeneity. Monetary evaluation of the psychic costs of various life events will also be carried out. In Section 3, we will test if individual satisfaction is dependent upon comparison income as well as upon absolute income and will attempt to find the strongest reference group for employees. Section 4 then concludes our findings.

II. Empirical Analysis of the Determinants of Individual Life Satisfaction

1. The Data

The data we will use come from the Korean Labor and Income Panel Study (KLIPS) provided by the Korea Labor Institute. KLIPS is comparable to the well-known panel studies in developed countries, such as the National Longitudinal Survey (NLS), the National Longitudinal Survey of Youth (NLSY), and the Panel Study of Income Dynamics (PSDI) in the U.S., the British Household Panel Study (BHPS) in the U.K., and the German Socio-Economic Panel (GSEP) in Germany. Although the range of socio-economic variables that KLIPS covers is as large as most of the longitudinal surveys mentioned above, its history is relatively short, with its first survey begun in 1998.

KLIPS originally surveyed a total of 13,738 individuals from 5,000 households in 1998, the year of its launch. About 3,862 of the original 5,000 households were followed up to the sixth wave in 2003, resulting in a retention rate of about 75%. The rest 25% of the households were replaced by new households each year, to keep the number of households annually surveyed steady at 5,000. In this paper, we will only use the sample of individuals who were consistently followed from the beginning of the study in 1998 up to the sixth wave in 2003. Although data up to the seventh wave are available, our empirical analysis will only make use of the five-year data from 1998 to 2002, because one of the most important variables of investigation, annual family income, is reported with a year’s delay. For example, the annual household income in 2002 is found in the sixth survey conducted in 2003, and that in 2001 is found in the fifth survey conducted in 2002 and so on. Also, the seventh year's data is not yet a final version, so the 2004 data is not used for our present analysis.

KLIPS contains such personal background information as the employment status, educational background, gender, residential area, the number of adults and children in the household, homeownership, religion, marital status, and age, among others. It also contains individual responses to a set of job satisfaction questions for employees, and life satisfaction questions for all individuals. The crucial economic variables such as individual wages and the total household wages and non-labour income are recorded each year as well.

2. Derivation of Variables

a. Life Satisfaction Measures

Each year, KLIPS asks a set of satisfaction questions in its individual questionnaires. The question appeared on the first wave of the KLIPS, directly translated to English, looks like the following:

Q) How satisfied are you with each category? Please circle the appropriate answer.

	Very Satisfied	Satisfied	Normal	Dissatisfied	Very Dissatisfied
Life Overall	1	2	3	4	5
Family Income	1	2	3	4	5
Family Relation	1	2	3	4	5
Leisure Activities	1	2	3	4	5
Living Environment	1	2	3	4	5

The first and the second waves of KLIPS ask exactly the same questions on satisfaction, with four sub-categories including family income, family relation, leisure activities, and living environment, in addition to the overall life satisfaction question as shown above. In the raw data, “very satisfied” was coded to one, “satisfied” was coded to two, and so on, with the highest value of five assigned to the response, “very dissatisfied”. However, KLIPS added two additional satisfaction questions to those original five beginning in 2000. These include a satisfaction question on the “relationship with relatives and friends” category, and another on “social relationship”. Responses to these additional variables, however, will be not used for our analysis because we want to derive a life-satisfaction measure that is consistent across the five-year period.

To come up with a variable that captures life satisfaction, not dissatisfaction, we initially recoded each response in reverse order. That is, "very satisfied" was recoded to five, whereas "very dissatisfied" was recoded to one, with "satisfied" and "dissatisfied" changing positions in the pecking order. Although we could simply ignore the subcategories of satisfaction questions and only use answers to the "overall" satisfaction with life question, we found that the range of this variable is too limited. In order to exploit the richness of the KLIPS data, we instead calculated the sum of the answers to the four different subcategory questions so that the variable can range from four to twenty, with 20 being the highest score of life satisfaction. This procedure is in fact similar to what was attempted by Clark and Oswald (1994, 2002) and Korpi (1997), who arbitrarily added sub-scores to come up with an overall score of well-being. One advantage we gain in having a variable with a scale of four to twenty instead of one to five is that it reflects more detailed approximation of individual satisfaction. Having a wider-range dependent variable would be especially helpful when we estimate fixed effects models later, because we can observe more cases with changes in this variable. On a final note, we find that the correlation coefficient between this calculated sum and the overall life satisfaction score stands high at 0.67.

b. Household Income Variables

KLIPS reports average monthly or annual household wages and detailed information on the amount and the source of annual non-labour income of the previous year. The questionnaire divides non-labour income into a total of sixteen sub-categories with major ones being financial income, real estate income, social security income, and transfer income. To calculate the total annual household income for the first two years, we multiplied the average monthly household wages by twelve, and added this to the sum of all non-labour income received. For the later three years, annual household wages were reported directly, and they were simply added to the total annual non-labour income. Finally, the calculated annual household income was adjusted for inflation using the regional CPI data each year, provided by the Korea National Statistical Office.[3]

[3]The base year is 2000. (CPI in 2000 = 100)

c. Other Variables of Interest

Education: A total of three education dummies were created, each for high school graduates (total years of education between 12 and 13 years), two-year college graduates (14 to 15 years), and those with four-year university education or higher (16 years or more). The omitted category is those with less than a high school diploma.

Religion: Based on the information provided in the very first wave of the survey, we created four dummies, each for Protestants, Catholics, Buddhists, and all other religions. The omitted category is those who do not have any religion.

Employment Status: Four dummies were created for the self-employed, employees, family workers, and the unemployed. Family workers are those who work at the family-owned businesses but do not officially get paid. The omitted category is those out of the labour force, who did not seek for jobs within one month of the survey date.

Marital Status: Four dummies were created for the married, separated, divorced, and the widowed. The omitted category is those who have never been married.

Other Variables: We have created 15 regional dummies to control for regional differences, as well as time dummies, to capture time effects. Other variables of interest include a female dummy, age, age squared, a homeowner dummy, the number of children, and the number of household members. Table 1 lists the names and the description of most key variables to be used for our preliminary analysis.

2. Final Sample for Estimation

The sample of individuals who were consistently followed through the sixth wave initially numbered 7,004. To further eliminate any inconsistency in the data, those who reported a sudden increase in education of three years or more, as well as those whose years of education decreased over time were dropped from the sample. The data containing no responses to our key variables including the total household income, employment status, life satisfaction, and such were further dropped. Consistency checks were also performed on the household income variable, and we dropped the data of those who reported their total household income

Table 1- Definition of Key Variables	
Variable Name	*Definition*
LifeSat	Life Satisfaction Score on a scale of 4 to 20
Female	Female Dummy: 1 if female
Protestant	Religion Dummy: 1 if Protestant
Catholic	Religion Dummy: 1 if Catholic
Buddhist	Religion Dummy: 1 if Buddhist
other_religion	Religion Dummy: 1 if All Other Religion
Age	Age
age_squared	Age Squared
Student	Student Dummy: 1 if still in school
Selfemp	Employment Dummy: 1 if self-employed
Familyworker	Employment Dummy: 1 if a family worker
Employee	Employment Dummy: 1 if an employee
Unemployed	Employment Dummy: 1 if unemployed
Married	Marital Dummy: 1 if married
Divorced	Marital Dummy: 1 if divorced
Separated	Marital Dummy: 1 if separated
Widowed	Marital Dummy: 1 if widowed
num_hhd	Number of household members
Num_Child_pre	Number of pre-school children aged under 7
Num_Child_old	Number of children aged 7 or older
Homeowner	Homeowner Dummy: 1 if home is owned
edu_highschool	Education Dummy: 1if between 12 and 13 years of education
edu_college	Education Dummy: 1if 14 and 15 years of education
edu_univ	Education Dummy: 1if 16 years of education or higher
Hhd_Income	Total annual household income in ten thousand Korean Won (in real terms)
ln_Hhd_Income	Natural Logarithm of Hhd_Income
2nd_quintile	Income Dummy: if Hhd_Income falls in the 2nd quintile of the sample
3rd_quintile	Income Dummy: if Hhd_Income falls in the 3rd quintile of the sample
4th_quintile	Income Dummy: if Hhd_Income falls in the 4th quintile of the sample
5th_quintile	Income Dummy: if Hhd_Income falls in the 5^{th} (highest) quintile of the sample

significantly lower than their own wages. Since even a small measurement error can lead to a severe bias in fixed-effect estimations, our careful deletion of somewhat large amount of inconsistent data was necessary. This procedure left us with a final sample of 5,947 individuals suitable for empirical analysis. The descriptive statistics of the key variables in the final sample are shown in Table 2.

3. Estimation of Life Satisfaction Equations

Table 2- Descriptive Statistics				
29,735 Observations (5,947 individuals)				Years pooled 1998-2002
Variable Name	*Mean*	*Std. Dev.*	*Min*	*Max*
LifeSat	12.219	2.255	4	20
Female	0.535	0.499	0	1
Protestant	0.193	0.395	0	1
Catholic	0.072	0.258	0	1
Buddhist	0.289	0.453	0	1
other_religion	0.014	0.119	0	1
Age	43.245	15.854	15	96
age_squared	2121.460	1494.439	225	9216
Student	0.105	0.307	0	1
Selfemp	0.163	0.370	0	1
familyworker	0.047	0.212	0	1
employee	0.364	0.481	0	1
unemployed	0.044	0.204	0	1
married	0.714	0.452	0	1
divorced	0.010	0.100	0	1
separated	0.006	0.078	0	1
widowed	0.073	0.261	0	1
num_hhd	3.912	1.295	1	10
Num_Child_pre	0.299	0.626	0	3
Num_Child_old	0.679	0.878	0	5
homeowner	0.668	0.471	0	1
edu_highschool	0.381	0.486	0	1
edu_college	0.089	0.285	0	1
edu_univ	0.126	0.332	0	1
Hhd_Income	2542.219	2718.301	2.793	116088.600
ln_Hhd_Income	7.512	0.901	1.027	11.662
2nd_quintile	0.199	0.400	0	1
3rd_quintile	0.204	0.403	0	1
4th_quintile	0.196	0.397	0	1
5th_quintile	0.200	0.400	0	1

a. Estimation Strategy

We begin by running pooled regressions on life satisfaction over five years. In doing so, we employ two different estimation techniques under two different assumptions. First, we will estimate the following life satisfaction equation of the form:

$$LS_{it}^* = \mathbf{x}_{it}\boldsymbol{\beta} + u_{it} \tag{1.1}$$

where LS_{it}^* is a latent variable indicating true life satisfaction for person i at time t that cannot be observed by econometricians, $\mathbf{x}_{it}$ is a vector of observable personal characteristics such as family income, martial status, education, age, gender, etc, $\boldsymbol{\beta}$ is a vector of corresponding estimation parameters, and u_{it} is the error term with a standard normal distribution, N(0,1). The reason why we have a latent variable in (1.1) is that we are assuming observed life satisfaction scores are only interpersonally "ordinally" comparable. The cardinality of the observed scores is not assumed here. The above model will be estimated using ordered probit with the following additional assumption:

$$\begin{aligned}
&LS_{it} = 4 \text{ if } LS_{it}* \le \alpha_1 \\
&LS_{it} = 5 \text{ if } \alpha_1 < LS_{it}* \le \alpha_2 \\
&\qquad\vdots \\
&LS_{it} = 20 \text{ if } LS_{it}* > \alpha_N
\end{aligned} \tag{1.2}$$

where LS_{it} is an observed response variable for life satisfaction on a scale of four to twenty, with twenty being the highest, α_i 's are unknown cut points (threshold parameters) that determine the mapping from $LS_{it}*$ to LS_{it} . In the ordered probit model, response probabilities can be simply calculated as follows:

$$\begin{aligned}
&P(LS_{it} = 4 \mid \mathbf{x}_{it}) = \Phi(\alpha_1 - \mathbf{x}_{it}\boldsymbol{\beta}) \\
&P(LS_{it} = 5 \mid \mathbf{x}_{it}) = \Phi(\alpha_2 - \mathbf{x}_{it}\boldsymbol{\beta}) - \Phi(\alpha_1 - \mathbf{x}_{it}\boldsymbol{\beta}) \\
&\qquad\vdots \\
&P(LS_{it} = 19 \mid \mathbf{x}_{it}) = \Phi(\alpha_{16} - \mathbf{x}_{it}\boldsymbol{\beta}) - \Phi(\alpha_{15} - \mathbf{x}_{it}\boldsymbol{\beta}) \\
&P(LS_{it} = 20 \mid \mathbf{x}_{it}) = 1 - \Phi(\alpha_{16} - \mathbf{x}_{it}\boldsymbol{\beta})
\end{aligned} \tag{1.3}$$

where Φ represents the standard normal distribution. Therefore, the log-likelihood function that we maximize can be written as the following:

$$\begin{aligned}
L = {}& 1[LS_{it} = 4]\ln[\Phi(\alpha_1 - \mathbf{x}_{it}\boldsymbol{\beta})] + 1[LS_{it} = 5]\ln[\Phi(\alpha_2 - \mathbf{x}_{it}\boldsymbol{\beta}) \\
& - \Phi(\alpha_2 - \mathbf{x}_{it}\boldsymbol{\beta})] + \ldots + 1[LS_{it} = 19]\ln[\Phi(\alpha_{16} - \mathbf{x}_{it}\boldsymbol{\beta}) \\
& - \Phi(\alpha_{15} - \mathbf{x}_{it}\boldsymbol{\beta})] + 1[LS_{it} = 20]\ln[1 - \Phi(\alpha_{16} - \mathbf{x}_{it}\boldsymbol{\beta})]
\end{aligned} \tag{1.4}$$

Alternatively, we will also estimate life satisfaction equations using pooled-OLS. The use of pooled-OLS, rather than ordered probit requires a strong assumption that life satisfaction scores are interpersonally "cardinally" comparable. In the ordered probit model with a latent variable, we assumed that the scores are just ordinal- i.e. we did not assume that a difference between a score of 4 and 8 is exactly twice as important as that between 4 and 6, 6 and 8, or 10 and 12. The estimation of life satisfaction equations using pooled-OLS, thus, accepts full cardinality of life satisfaction scores. Despite its strong assumption, we find that a number of previous research employed OLS estimation techniques; these include Korpi (1997), Di Tella, MacCulloch, and Oswald (2001), Helliwell (2001), Clark and Oswald (2002), Graham, Eggers, and Sukhtankar (2003), among others.

Now, the life satisfaction model we will estimate using pooled OLS is as follows:

$$LS_{it} = \mathbf{x}_{it}\boldsymbol{\beta} + u_{it} \tag{1.5}$$

where LS_{it} is a life satisfaction score for person i at time t that is observed by econometricians, $\mathbf{x}_{it}$ is a vector of personal characteristics, $\boldsymbol{\beta}$ is a vector of corresponding estimation parameters including an intercept, and u_{it} is the error term.[4)] Thus, (1.5) implies that life satisfaction scores are not the result of mapping from an unobservable latent variable, but the true satisfaction is directly observable.

b. Estimation Results

Results from both ordered probit and pooled-OLS regressions are reported in Table 3. For the regression shown in the first column, we used income quintile dummies, while for the second column we used the natural log of household income as explanatory variables for family income. All non-income related explanatory variables are the same for both. Since both regression results gave us similar parameter estimates, we will focus mostly on our results reported in the second column, when discussing non-income effects.

Although it is impossible to directly compare the coefficients from the ordered probit estimation against those from the OLS estimation within each column, it can be immediately seen that the results are identical in the direction of effects. The explanatory variables found significant in one model are also significant in another, suggesting the robustness of our results. Moreover, the estimated t-statistics show that almost all of our explanatory variables have significant effects on individual life satisfaction. First, as was suggested by Winkelmann and Winkelmann (1998), Clark and Oswald (2002) and others, the large negative effect on life satisfaction of unemployment stands out. The OLS coefficient on unemployment is -0.76. This means that, compared to employees, rather than to those out of the labour force, (the

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[4)] In the previous ordered probit model, however, $\boldsymbol{\beta}$ does not include a constant because α_1 can act as an intercept instead. For more details, see Wooldridge (2002), p.505.

Table 3

Parameter Estimates for the Life Satisfaction Equation

No.Observation: 29,735 Years pooled 1998-2002

	(1)		(2)	
Explanatory Variables	*Ordered Probit*	*OLS*	*Ordered Probit*	*OLS*
Female	-0.015	-0.033	-0.008	-0.020
	(-0.014)	(-0.028)	(-0.014)	(-0.028)
Age	-0.031	-0.061	-0.034	-0.068
	(0.003)**	(0.007)**	(0.003)**	(0.007)**
age_squared	0.000	0.001	0.000	0.001
	(0.000)**	(0.000)**	(0.000)**	(0.000)**
Protestant	0.031	0.059	0.030	0.057
	(0.017)+	(0.034)+	(0.017)+	(0.034)+
Catholic	0.077	0.158	0.092	0.188
	(0.024)**	(0.048)**	(0.024)**	(0.049)**
Buddhist	0.045	0.092	0.041	0.085
	(0.014)**	(0.029)**	(0.014)**	(0.029)**
other_religion	0.024	0.050	0.018	0.036
	(-0.050)	(-0.100)	(-0.050)	(-0.099)
Student	0.124	0.252	0.114	0.231
	(0.026)**	(0.051)**	(0.026)**	(0.051)**
Selfemp	-0.180	-0.356	-0.190	-0.378
	(0.020)**	(0.039)**	(0.020)**	(0.040)**
Familyworker	-0.219	-0.423	-0.235	-0.457
	(0.030)**	(0.059)**	(0.030)**	(0.059)**
Employee	-0.117	-0.230	-0.120	-0.238
	(0.016)**	(0.032)**	(0.016)**	(0.033)**
Unemployed	-0.374	-0.751	-0.377	-0.758
	(0.032)**	(0.066)**	(0.032)**	(0.066)**
Married	0.280	0.561	0.284	0.569
	(0.031)**	(0.062)**	(0.031)**	(0.062)**
Divorced	-0.222	-0.457	-0.208	-0.429
	(0.064)**	(0.133)**	(0.065)**	(0.133)**
Separated	-0.345	-0.717	-0.348	-0.724
	(0.080)**	(0.168)**	(0.082)**	(0.171)**
Widowed	0.120	0.240	0.158	0.318
	(0.044)**	(0.088)**	(0.043)**	(0.088)**
num_hhd	-0.081	-0.161	-0.081	-0.162
	(0.006)**	(0.012)**	(0.006)**	(0.012)**
Num_Child_pre	0.034	0.064	0.034	0.066
	(0.013)*	(0.026)*	(0.013)**	(0.026)*
Num_Child_old	-0.010	-0.022	-0.006	-0.012
	(-0.009)	(-0.018)	(-0.009)	(-0.018)

Table 3- continued

Explanatory Variables	*Ordered Probit*	*OLS*	*Ordered Probit*	*OLS*
Homeowner	0.294	0.593	0.315	0.634
	(0.014)**	(0.028)**	(0.014)**	(0.028)**
edu_highschool	0.172	0.341	0.189	0.376
	(0.016)**	(0.033)**	(0.016)**	(0.033)**
edu_college	0.272	0.533	0.313	0.614
	(0.025)**	(0.051)**	(0.025)**	(0.051)**
edu_univ	0.471	0.930	0.514	1.015
	(0.023)**	(0.045)**	(0.022)**	(0.044)**
2nd_quintile	0.347	0.701		
	(0.020)**	(0.041)**		
3rd_quintile	0.556	1.116		
	(0.021)**	(0.041)**		
4th_quintile	0.782	1.562		
	(0.022)**	(0.043)**		
5th_quintile	1.041	2.067		
	(0.023)**	(0.045)**		
Ln_Hhd_Income			0.392	0.782
			(0.009)**	(0.018)**
Constant		13.308		8.219
		(0.485)**		(0.410)**
(Pseudo) R-squared	0.05	0.20	0.05	0.19
_cut1	-3.749	(0.283)	-1.215	(0.242)
_cut2	-3.527	(0.282)	-0.988	(0.240)
_cut3	-3.213	(0.281)	-0.670	(0.239)
_cut4	-2.902	(0.280)	-0.355	(0.239)
_cut5	-2.438	(0.280)	0.113	(0.238)
_cut6	-1.996	(0.280)	0.558	(0.238)
_cut7	-1.511	(0.280)	1.043	(0.238)
_cut8	-1.008	(0.280)	1.545	(0.239)
_cut9	-0.402	(0.280)	2.147	(0.239)
_cut10	0.058	(0.280)	2.605	(0.239)
_cut11	0.531	(0.280)	3.075	(0.239)
_cut12	1.013	(0.280)	3.555	(0.239)
_cut13	1.796	(0.280)	4.337	(0.240)
_cut14	2.123	(0.281)	4.663	(0.240)
_cut15	2.371	(0.282)	4.909	(0.242)
_cut16	2.562	(0.283)	5.099	(0.243)

Heteroscedacity-robust standard errors are in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

Notes:
In addition to the explanatory variables listed above, 15 region dummies and 4 time dummies are also included in both regressions.

omitted category), the unemployed report life satisfaction scores that are on average 0.52 point lower, under the condition that all other characteristics are identical. Another interesting finding is that the out-of-the-labour force status provides a lot more happiness than any other employment status does. These non-working but not-seeking individuals are 0.38 point more satisfied than the self-employed and 0.24 point more satisfied than employees, holding other characteristics constant. Therefore, we conclude that the non-working individuals who do not seek jobs experience higher life satisfaction than the working individuals or the unemployed, holding other factors constant.

According to Table 3, life satisfaction is "U-shaped" in age, reaching a minimum at the age of about 47-48. Among different religions, Catholics are the happiest, followed by Buddhists and Protestants. The coefficients on Catholics and Buddhists are significant at the 1% level. Studentship also has a positive and significant effect on life satisfaction. One of the most important events in life, marriage, has a positive effect, as is commonly believed. The incidence of divorce or separation, on the other hand, produces disutility. In the case of separation, the magnitude of the coefficient is the second largest among the negatives, next to unemployment. Both our ordered probit and OLS estimates suggest that the incidence of separation has an approximately 1.3 times larger effect than that of divorce. This finding is consistent with the idea that people adjust to their unfortunate situation as time goes by, as separation usually precedes divorce. By contrast, the widowhood has, somewhat surprisingly, a positive effect on well-being. Of course, it just means that the widowed are more satisfied with life than singles. Compared to the married, they are unhappier, holding other factors constant.

The number of pre-school children variable is found to increase life satisfaction, although the magnitude is small. Perhaps the positive aspects of having a little child slightly outweigh the associated costs. The negative effect of the number of household members variable is in contrast to some findings of the "economy of size" in subjective well-being, such as Diener, *et al.* (1999) and Ravallion and Lokshin (2000). Our finding suggests that the larger the family, the lower becomes the individual's life satisfaction, holding other factors constant.

Moreover, homeownership is found to have a significant effect on subjective welfare. Its coefficient is even larger than that on marriage. This is a somewhat shocking result because we controlled for other characteristics of individuals including family income. Unusually high real estate prices in Korea and the immense difficulty for an average household to own a house or an apartment should all contribute to this result. Real estate prices are exorbitantly high in

Korea due to a high population density, and the rising house prices have consistently been an important issue over the past twenty years or so. There was even a private report released in 2005 that it would take more than forty years for an average household to buy a regular-sized (approximately 106 square meters) apartment in Seoul under the condition that they keep saving their income net of average expenses every single year (Lee 2005). If homeownership has this huge effect on individual subjective welfare, then the Korean government should aim to provide more houses at affordable prices to raise its citizens' well-being. The recent measures taken by the government in 2005 to cool down the rising real estate prices should thus be viewed as an appropriate policy from the subjective welfare's stand point.

The estimation results of the education dummies also show interesting findings. Controlling for income did not render the education effect insignificant. Compared to those with less than high school education, individuals with a high school diploma but less than a two-year college degree enjoy 0.38 point of more life satisfaction (OLS estimate), holding other factors constant. The coefficient on education dummies increases as we move to higher education categories. Thus, this finding is consistent with an idea that people with more years of education derive extra satisfaction from a rise in status or others' positive perception towards them, independently of income. If they are perceived to be smarter due to more years of education, this kind of good perception and recognition could indeed make them happier. A highly paid individual may still feel inferior if his educational background is below average. Thus, this positive effect of education can be thought to reflect a rise in self-esteem or status associated with an increase in the education level.

Finally, family income is found to have the largest effect on subjective welfare. Holding other factors constant, individuals whose family income falls in the top quintile of the sample enjoy almost 2 more points' worth of life satisfaction on a 17-point scale. This is a huge impact. Just like education, the coefficients on income quintile dummies increase almost monotonically from the lowest to the highest category. The ordered probit coefficients on income dummies suggest that a sudden move from the lowest income quintile to the highest income quintile can potentially change an individual's life satisfaction level from 4 to 8, or from 17 to 20. The large positive effect on subjective well-being is thus confirmed by this result. By far, income is the most important determinant of life satisfaction.

The OLS result gives the log income variable a coefficient of 0.78, with a t-statistic as large as 42. What it suggests is that a 100% increase in income would increase the satisfaction score by 0.78 point on average. Unemployment has a coefficient of -0.76, and the employee's is -0.24. The utility difference between the two is thus -0.52. Hence, to compensate for the negative impact of a status change from being employed to unemployed, a 67% increase in income is needed. The same calculation using the ordered probit results gives the same figure- income should increase by 67% to compensate for the psychological loss from being unemployed. This calculation, of course, does not take into account the fact that the change in status from being employed to unemployed also brings about a decline in family income. But still, our number is meaningful in a sense that it represents the non-pecuniary cost of unemployment. If we use the average family income in the sample, KRW 25.4 million, the average non-pecuniary cost of unemployment is estimated to be about KRW 17 million in terms of annual family income.

Our calculation method can be used to derive the non-pecuniary cost of other life events as well. For example, let's look at the huge negative coefficient of -0.73 on separation. Its difference with the coefficient on the married is as large as 1.29. Hence, a 165% increase in annual family income per head would be needed to completely offset the well-being loss from separation. (this figure does not even consider the monetary loss from separation) In the case of divorce, the cost is about 128% of income. Thus, we conclude that the psychological cost of marital separation or divorce is much larger than that of unemployment.

c. Individual Heterogeneity and the Fixed Effects Estimation

So far, we have ignored the possible problem of individual heterogeneity in estimating life satisfaction equations. The presence of individual specific effects can lead to biased parameter estimates. For example, people with different personality traits might interpret the satisfaction scales differently. How can we be sure that one person's 5 has the same meaning as another's 5? Maybe with the same level of life satisfaction, one could answer 5, but another 7? In this case, responses are not interpersonally comparable, and it would be necessary to look at the changes in responses of the same people, rather than at the differences in responses across the population.

Some people may be even born happy. If there is an individual-specific characteristic that we cannot observe and it is correlated with other explanatory variables, then our parameter estimates can be biased. For example, a person born with a trait that makes him happy may be likely to have more education, to be more productive at work, or to become a Catholic. Then the estimated effect of education, income, or religion can all suffer from the endogeneity bias. In fact, psychologists Lykken and Tellegen (1996) argue that as much as 80% of the variations in well-being are determined by the heritable qualities, after examining the twins survey in the U.S. De Neve and Cooper (1999) also cite 137 personally traits that are correlated with subjective well-being. If these personality traits are correlated with explanatory variables, then not accounting for these unobserved factors can lead to a bias.

If we represent the unobserved individual-specific effect as c_i, then our empirical specification would look like the following:

$$LS_{it} = \mathbf{x}_{it}\boldsymbol{\beta} + c_i + u_{it} \tag{1.6}$$

where LS_{it} is a life satisfaction score for person *i* at time *t* that is observed by econometricians, $\mathbf{x}_{it}$ is a vector of personal characteristics, $\boldsymbol{\beta}$ is a vector of corresponding estimation parameters including an intercept, and u_{it} is the error term. Our previous pooled-OLS model implicitly assumed that there is no correlation between $\mathbf{x}_{it}$ and c_i. Thus, for the pooled-OLS estimates to be consistent, the conditions $\mathrm{E}(\mathbf{x}'_{it}u_{it}) = \mathbf{0}$ and $\mathrm{E}(\mathbf{x}'_{it}c_i) = \mathbf{0}$ should be met. If not, then the fixed effects (within) estimation should be used in order to eliminate the endogeneity bias arising from time-invariant individual-specific effects.

The fixed effects estimation, however, cannot avoid all sources of endogeneity bias. One example is the time-variant unobserved individual characteristics. Diener, *et al.* (1999), for example, report that the responses to subjective well-being questions are affected by the mood of the individuals at the time of the interview. It is possible that even a generally happy person would feel gloomy during the certain time of the day. Whether the survey was conducted during the day or evening can also be a factor. Therefore, if there is any inconsistency in the time the interview was conducted, or the questionnaire were completed, responses to subjective questions can be altered.

Another source of endogeneity bias is simultaneity. Let us consider unemployment. Although the negative effect of unemployment on individual welfare can be estimated, one can argue that there might be a reverse causality. According to this argument, it is not only that the unemployed are less happy but also that the less happy are more likely to get unemployed. Thus, the estimated effect of unemployment on well-being can be, in fact, misleading. The same argument can also be applied to any other explanatory variable: Income increases happiness, but happy people might also earn more. In order to control for simultaneity, one would need an instrumental variable that is correlated with unemployment or income but not with happiness. At present, such a variable is almost impossible to find. A better solution would be to use data from a natural experiment, such as an abrupt change in employment status due to a plant closure, etc. But the natural experiment data that contain life satisfaction responses are not readily available, either. Therefore, we would like to note that our employment of fixed effects estimation cannot completely resolve the issue of endogeneity bias. What we can control for, however, is the time-invariant individual-specific effects. If our fixed effects estimation results that control for time-invariant individual heterogeneity come out to be similar to those of our previous pooled estimations, then the support for interpersonal comparability of life satisfaction responses can be strengthened.

Some previous research using longitudinal data, including Winkelmann and Winkelmann (1998) and Hamermesh (2001), employ the conditional likelihood estimation approach, developed by Chamberlain (1980). Chamberlain's model is actually a binomial fixed-effects logit model. In order to make use of this technique, one has to make the dependent variable binary. For example, Winkelmann and Winkelmann (1998) recode any satisfaction response above seven to one, and to zero otherwise. The amount of data one can lose from this procedure can be huge since the fixed effects estimation uses information on only the data that register changes in both the dependent variable and the explanatory variables of interest, to identify parameters. Winkelmann and Winkelmann observe only 2,523 individuals who move their binary satisfaction status over time, out of 10,000 individuals. This is a huge loss of data. Suppose an individual's actual well-being level dropped from 6 to 1 in their data after being unemployed. Since they made the dependent variable binary, a change from 6 to 1 on an actual scale constitutes no change on a binary scale. Therefore, in order to avoid the data loss and make use of the richness of our dataset, we will not attempt to estimate the life satisfaction equation using the fixed-effects logit model developed by Chamberlain (1980). Rather, we will focus on the standard fixed-effects regression, assuming the full cardinality of subjective well-being measures.

The results from our fixed-effects estimation are shown in Table 4. Immediately, a number

Table 4

Parameter Estimates for the Life Satisfaction Equation – Fixed Effects

No. Observation: 29,735

Explanatory Variables	*Coefficients*	*Standard Errors*
Age	0.0671	(0.0246)**
age_squared	-0.00026	(0.00025)
Student	0.161	(0.054)**
Selfemp	-0.159	(0.067)*
Familyworker	-0.221	(0.091)*
Employee	0.005	(0.046)
Unemployed	-0.347	(0.061)**
Married	0.271	(0.138)+
Divorced	-0.033	(0.243)
Separated	-0.547	(0.276)*
Widowed	0.286	(0.195)
num_hhd	-0.078	(0.024)**
Num_Child_pre	0.028	(0.045)
Num_Child_old	-0.035	(0.032)
Homeowner	0.265	(0.049)**
edu_highschool	-0.115	(0.106)
edu_college	-0.010	(0.146)
edu_univ	0.225	(0.199)
ln_Hhd_Income	0.165	(0.020)**
Constant	11.092	(1.765)**

$F(37,23751) = 11.23$

R-squared: within= 0.0172 between= 0.0117 overall= 0.0092

+ significant at 10%; * significant at 5%; ** significant at 1%

Notes:

Although not shown, 15 region dummies and 3 time dummies in are also included in the fixed-effects regression.

of differences from our previous results can be observed. First, the “U-shaped” age effect no longer holds. Age now has a positive and significant effect, and the age squared has a negative effect, meaning that satisfaction is “inverse U-shaped” in age. Contrary to our result, Winkelmann and Winkelmann (1998) report a negative effect of age using the German panel data, and Clark and Oswald (2002) still find a “U-shaped” age effect from the fixed-effects regression. The reason for the discrepancy in findings is not clear.

The negative effect of unemployment survives, but its magnitude is reduced to -0.35. Becoming a family worker also causes an individual to experience a loss of satisfaction. The effect of martial separation on well-being is still large, with the coefficient on the separated of about -0.55, although that of divorce is now insignificant. The effect of marriage is 0.27 and is significant at the ten percent level. Another contrasting result is the coefficient on education. In our previous estimation, the coefficients on all of the education dummies were positive and significant. However, now education seems to play no role in subjective welfare. Perhaps the reason is that the number of individuals who changed their education status over the five years was very small, and the small sample size may have generated this contrasting result. A lack of many changes in one variable in the fixed-effects estimation can undoubtedly lead to spurious results. Therefore, we suspect that this should be the primary reason why the education effect was not identified in the fixed-effects estimation.

The income effect also is reduced in size to 0.17 from 0.78 but is still significant. The reduction of its coefficient in the fixed-effects estimation supports Easterlin's (2001) hypothesis that individual happiness does not change much over time as income increases due to rising aspiration levels, but the initial gap between the poor and rich remains large, as is observed in cross-sections. This discrepancy between our pooled- and fixed-effects regression results, therefore, can be thought of as a supporting evidence for Easterlin's findings - individuals gain very little from changes in income over time, but at one point in time, the rich appear to enjoy much higher life satisfaction than the poor.

Of course, there is another explanation for the discrepancy between the two results- the presence of individual heterogeneity. Perhaps, the unobservables positively correlated with individual life satisfaction were also positively correlated with income. For example, as mentioned earlier, it might be the case that people born happy tend to earn higher wages. Not controlling for the unobservables, thus, can lead to the overestimate of the income effect. Since our fixed-effects estimation controlled for these time-invariant unobservables, the coefficient is now smaller, capturing only the pure income effect, independent of the effect of unobservables.

The fixed-effects result suggests that a 100% increase in income would increase the satisfaction score by 0.17 point. Hence, to compensate for the negative impact of a status change from being employed to unemployed, as much as 200% increase in annual family income is needed. In the case of separation, the figure stands at 480%. Using the mean annual family income of KRW 25.4 million, we can say that the average psychological cost of unemployment is about KRW 54.2 million, and that of separation is about KRW 126 million. Similarly, the benefits of positive life events such as marriage and homeownership can be evaluated in terms of family income. Through marriage, individuals gain additional life satisfaction equivalent to KRW 41.8 million in annual family income, and homeownership brings

Table 5- Monetary Evaluation of the Psychological Costs of Various Life Events - in terms of annual household income (in millions of KRW)

	Pooled-OLS	Fixed-Effects
Costs		
Divorce	32.44	**46.84**
Widowhood	8.16	**-(2.31)**
Separation	42.03	**126.03**
Employee→ Unemployed	16.91	**54.23**
Benefits		
Single→ Married	18.50	**41.75**
Home-renter→ Home-owner	20.61	**40.83**
Non-student→ Student	7.51	**24.81**

Note:
Figures were evaluated at the mean annual household income of KRW 25.42 million.

in additional satisfaction worth KRW 40.8 million. Our calculations of these psychological costs and benefits of various life events are shown in Table 5.

It would be interesting to compare these costs of divorce and separation with the actual alimony paid to divorced women in Korea. According to a survey of 115 divorced Korean women conducted in 2003 jointly by *Donga Weekly* and Sunwoo, a famous match-making company, the divorced women received KRW 49.6 million of alimony on average (Kim 2003). However, when these same women were asked the following question, "how much alimony would you actually want?" the average of their answers was much higher at about KRW 168.4 million. Not surprisingly, a whopping 66% of the respondents said their alimony received was not sufficient, and many claimed that the psychological pain they suffered is worth more than what they received. Our calculation of the average psychological cost of separation and divorce based on the fixed-effects estimation, KRW 172 million (=126+46), is surprisingly close to the average amount of alimony divorced women actually wanted when asked afterwards. Considering that separation usually precedes divorce, the amount to compensate for the psychological pain of these women should take into account their utility loss from both separation and divorce. Thus, what our calculation suggests is that the average amount of alimony the divorced women in Korea claim is not out of line with their utility loss evaluated in terms of income. It seems evident that the current level of alimony actually paid to divorced women in Korea is too low for their psychological pain to be fully compensated for.

III. The Effect of Comparison Income and the Reference Group

1. Comparison Income

Individual life satisfaction may be dependent upon not only one's own income but also his comparison income. In order to test the effect of comparison income on individual well-being, we calculated the arbitrary reference group's annual household income. The data we used to create this comparison income variable come from the 2000 Korean Household Consumption Survey conducted by the Korea National Statistical Office[5]. This national survey data reports average household income by both region and household size - it divides the household region into 16 different categories and the household size into 6. Therefore, a total of 96 different values for the comparison income could be created for our sample. This survey, however, is conducted only once in every five years, which means that we could create this variable only for the year 2000. In order to see first that our regression results using only the year 2000 data are in line with our previous five-year pooled estimates, we regressed life satisfaction on the same explanatory variables as in Table 3. Table 6 reports our basic regression results.

As can be seen from the table, although we are using only one year of our sample, the parameter estimates remain quite similar in magnitude to those in Table 3. Life satisfaction is again "U-shaped" in age, reaching a minimum at about 45, unemployment and marital separation have the two largest negative effects, marriage and homeownership have large positive effects, the self-employed and family workers report less satisfaction, and both income quintiles and education play a significant role in determining subjective welfare. The effect of log income is slightly reduced to 0.61 but is statically significant with a t-statistic of 16.

Now, in order to capture the comparison effect, we added the natural logarithm of the comparison income variable newly created to our basic regression equation above. Since including this new variable did not change the coefficients on other explanatory variables, we choose to report only the parameter estimates for income-related variables. The result is presented in the first column of Table 7. As can be immediately seen, the inclusion of the comparison income variable did not change the coefficient on one's own household income- it stays constant at about 0.61. On the other hand, the coefficient on comparison income is negative but is not statistically significant. The effect of comparison income, therefore, cannot

[5]The 2000 Korean Household Consumption Survey is available at the following URL: http://www.nso.go.kr/newnso/s_data/j_potal_view.html?category_id=116

Table 6

Parameter Estimates for the Life Satisfaction Equation

No. Observation: 5,947 Year 2000 Only

	(1)		(2)	
Explanatory Variables	*Ordered Probit*	*OLS*	*Ordered Probit*	*OLS*
Female	0.023	0.041	0.036	0.065
	(-0.032)	(-0.059)	(-0.032)	(-0.060)
Age	-0.022	-0.041	-0.026	-0.049
	(0.008)**	(0.014)**	(0.008)**	(0.014)**
age_squared	0.000	0.000	0.000	0.001
	(0.000)**	(0.000)**	(0.000)**	(0.000)**
Protestant	0.058	0.110	0.051	0.098
	(-0.037)	(-0.069)	(-0.037)	(-0.07)
Catholic	0.058	0.111	0.078	0.149
	(-0.055)	(-0.102)	(-0.054)	(-0.102)
Buddhist	0.031	0.057	0.032	0.058
	(-0.033)	(-0.061)	(-0.033)	(-0.062)
other_religion	0.043	0.076	0.026	0.045
	(-0.109)	(-0.209)	(-0.111)	(-0.214)
Student	0.180	0.331	0.166	0.307
	(0.070)**	(0.129)*	(0.070)*	(0.131)*
Selfemp	-0.198	-0.359	-0.193	-0.354
	(0.045)**	(0.084)**	(0.045)**	(0.084)**
Familyworker	-0.290	-0.529	-0.283	-0.522
	(0.066)**	(0.124)**	(0.068)**	(0.127)**
Employee	-0.066	-0.116	-0.056	-0.099
	(0.036)+	(0.068)+	(-0.036)	(-0.069)
Unemployed	-0.261	-0.494	-0.284	-0.542
	(0.085)**	(0.162)**	(0.084)**	(0.160)**
Married	0.261	0.489	0.272	0.513
	(0.069)**	(0.129)**	(0.068)**	(0.128)**
Divorced	-0.102	-0.211	-0.082	-0.178
	(-0.166)	(-0.318)	(-0.161)	(-0.311)
Separated	-0.374	-0.704	-0.397	-0.756
	(0.171)*	(0.336)*	(0.173)*	(0.340)*
Widowed	0.147	0.275	0.184	0.346
	(-0.098)	(-0.184)	(0.097)+	(0.183)+
num_hhd	-0.081	-0.150	-0.074	-0.139
	(0.014)**	(0.026)**	(0.014)**	(0.027)**
Num_Child_pre	0.061	0.110	0.058	0.106
	(0.030)*	(0.056)*	(0.030)+	(0.057)+
Num_Child_old	-0.028	-0.050	-0.023	-0.042
	(-0.020)	(-0.037)	(-0.02)	(-0.038)

Table 6- continued				
Explanatory Variables	*Ordered Probit*	*OLS*	*Ordered Probit*	*OLS*
Homeowner	0.230	0.439	0.255	0.489
	(0.031)**	(0.059)**	(0.031)**	(0.059)**
edu_highschool	0.226	0.418	0.252	0.471
	(0.037)**	(0.070)**	(0.037)**	(0.070)**
edu_college	0.292	0.536	0.350	0.648
	(0.058)**	(0.108)**	(0.058)**	(0.109)**
edu_univ	0.499	0.919	0.575	1.068
	(0.050)**	(0.093)**	(0.050)**	(0.093)**
2nd_quintile	0.220	0.408		
	(0.045)**	(0.084)**		
3rd_quintile	0.540	1.013		
	(0.045)**	(0.084)**		
4th_quintile	0.659	1.236		
	(0.048)**	(0.089)**		
5th_quintile	1.003	1.856		
	(0.050)**	(0.091)**		
ln_Hhd_Income			0.327	0.614
			(0.020)**	(0.037)**
Constant	0.230	0.439	0.255	0.489
	(0.031)**	(0.059)**	(0.031)**	(0.059)**
(Pseudo) R-squared	0.05	0.19	0.05	0.18
_cut1	-3.442	(0.246)	-1.379	(0.278)
_cut2	-2.903	(0.201)	-0.820	(0.236)
_cut3	-2.562	(0.193)	-0.480	(0.230)
_cut4	-2.270	(0.189)	-0.190	(0.227)
_cut5	-1.751	(0.185)	0.326	(0.225)
_cut6	-1.337	(0.184)	0.737	(0.225)
_cut7	-0.822	(0.184)	1.250	(0.225)
_cut8	-0.262	(0.184)	1.804	(0.225)
_cut9	0.374	(0.184)	2.432	(0.226)
_cut10	0.860	(0.184)	2.913	(0.227)
_cut11	1.368	(0.185)	3.416	(0.227)
_cut12	1.898	(0.186)	3.939	(0.229)
_cut13	2.769	(0.194)	4.802	(0.235)
_cut14	3.175	(0.202)	5.211	(0.243)
_cut15	3.502	(0.223)	5.547	(0.263)
_cut16	3.794	(0.267)	5.843	(0.310)

Heteroscedacity-robust standard errors are in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

Notes:
In addition to the explanatory variables listed above, 15 region dummies are also included in both regressions.

Table 7- Relative Income Test
Income Parameter Estimates for the Life/Income Satisfaction Equations
No. Observation: 5,947 Year 2000

	(1)		(2)		(3)	
	Life Satisfaction		*Income Satisfaction*		*Income Satisfaction*	
Explanatory Variables	*Ordered Probit*	*OLS*	*Ordered Probit*	*OLS*	*Ordered Probit*	*OLS*
ln_Hhd_Income	0.329	0.617	0.457	0.286	0.196	0.126
	(0.020)**	(0.037)**	(0.024)**	(0.014)**	(0.107)+	(0.067)+
ln_Average_Income_by_Region	-0.099	-0.176	-0.261	-0.16		
	(-0.095)	(-0.181)	(0.107)*	(0.067)*		
Income_Difference					0.261	0.16
					(0.107)*	(0.067)*
(Pseudo) R-squared	0.05	0.18	0.05	0.19	0.05	0.19
_cut1	-2.072	(0.728)	-0.834	(0.784)	-0.834	(0.784)
_cut2	-1.515	(0.707)	0.649	(0.784)	0.649	(0.784)
_cut3	-1.175	(0.700)	2.268	(0.785)	2.268	(0.785)
_cut4	-0.886	(0.699)	4.000	(0.797)	4.000	(0.797)
_cut5	-0.369	(0.697)				
_cut6	0.042	(0.697)				
_cut7	0.554	(0.697)				
_cut8	1.108	(0.697)				
_cut9	1.737	(0.697)				
_cut10	2.217	(0.698)				
_cut11	2.721	(0.698)				
_cut12	3.244	(0.698)				
_cut13	4.107	(0.699)				
_cut14	4.516	(0.703)				
_cut15	4.852	(0.717)				
_cut16	5.148	(0.745)				

Heteroscedacity-robust standard errors are in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

Notes:
All non-income related explanatory variables listed in Table 6 are also included in these regressions, including region dummies.

be confirmed from our result in the first column.

Our regression for the second column of Table 7 makes use of an alternative dependent variable. The dependent variable we now use is a narrower concept of life satisfaction, namely income satisfaction. As mentioned earlier, KLIPS records individual income satisfaction on a scale from 1 to 5, with 5 being the highest. It was also one component of our life satisfaction score that ranged from 4 to 20. Since this score is supposed to captures individuals' satisfaction with respect to income only, we suspect that using this alternative measure as a dependent variable would allow us to more clearly capture the effect of comparison income.

The result shown in the second column confirms our suspicion. Individuals' own income and comparison income both have significant effects on their income satisfaction. Our OLS estimate suggests that a 100% rise in one's own income would increase his income satisfaction by 0.29 on a five-point scale, but if his comparison income also increases by 100%, then the overall increase would just be 0.13 (=0.29-0.16). However, the effect of comparison income is only about half the size of own income and is not as large as some previous researchers find.

For a final check, we additionally tested the comparison income effect using a different specification. This time, we calculated the difference between the two income variables and inserted it in our equation as an explanatory variable instead; the regression result using this alternative variable is shown in the third column of Table 7. It is worth noting that this specification is, in fact, econometrically identical to our specification in the second column. To illustrate this point, let us write the second column regression equation as follows:

$$\mathrm{IS_i} = \beta_0 + \beta_1 \ln(\mathrm{own\_income_i}) + \beta_2 \ln(\mathrm{comp\_income_i}) + \ldots + u_i \tag{1.7}$$

where $\mathrm{IS_i}$ refers to person i's income satisfaction, β 's are the parameters of interest, and u_i is an error term. Our third column equation can be similarly written as:

$$\mathrm{IS_i} = \gamma_0 + \gamma_1 \ln(\mathrm{own\_income_i}) + \gamma_2 \{\ln(\mathrm{own\_income_i}) - \ln(\mathrm{comp\_income_i})\} + \ldots + u_i \tag{1.8}$$

where γ 's are the parameters of interest. If we rearrange the terms on the right hand side of (1.8), it can become identical to (1.7) as follows:

$$\mathrm{IS_i} = \gamma_0 + (\gamma_1 + \gamma_2) \ln(\mathrm{own\_income_i}) - \gamma_2 \ln(\mathrm{comp\_income_i}) + \ldots + u_i \tag{1.9}$$

Hence, β_1 and β_2 in (1.9) are in fact equivalent to $\gamma_1 + \gamma_2$ and $-\gamma_2$ in (1.8). As is shown in Table 7, our employment of two different specifications generated virtually the same results- the comparison income effect is negative and is of about half the size of the own income effect. What we can conclude from our finding, thus, is that the comparison income does matter to one's income satisfaction - others' performance negatively affects my welfare relating to income. The effect, however, is much smaller than that of individuals' own income.

2. Employees' Reference Group

As mentioned earlier, previous economic research has not clearly addressed the issue of who is in the reference group. Specifically in the case of working individuals, would people compare their wages against those of similar age? It would indeed be reasonable to think that people look at their peers, not people 20 or 30 years older, when making comparisons. For example, an individual who just started work fresh out of college is more likely to compare himself against the people of the same age, not fifty-year olds. How about educational differences? Would a high school graduate compare his wage against someone with a Ph.D.? Not likely. Similarly, the type of occupation can be another strong factor influencing the composition of one's reference group. Farmers, for example, would not compare against investment bankers. The increase in the average salary in the investment banking industry would affect the job satisfaction of bankers more strongly than it would the satisfaction of farmers. Or it may well be that all of these factors are into play. People might compare against those with similar educational and occupation backgrounds, who are also in the same age group. But which of these factors has the strongest impact on the individual's formation of his reference group? Below, we will attempt to find an answer to this specific question.

a. The Data and the Derivation of Variables

The KLIPS data report monthly wages of employees in all of its survey years. We first adjusted the wage variable for inflation, using the regional CPI data each year provided by the Korea National Statistical Office. The data missing the wage information at any given year were dropped from the sample, as well as those with reported weekly working hours of less than five. This procedure left us with a total of 10,556 observations consisting only of "employees". The year of observation spans from 1998 to 2002. In addition, in order to create an average wage variable in each arbitrary reference group, we utilized the annual average salary information obtained from the Basic Statistical of Wage Structure, provided by the Ministry of Labor.[6] The Basic Statistical of Wage Structure data contain average monthly wage information by age, education, and occupation. It has a total of ten age group categories with the lowest category being the 19 years old or younger and the highest being the 60 years old or older. Education has four different categories- middle school or less, high school, two-

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[6] The Basic Statistical of Wage Structure is available at the following URL: http://laborstat.molab.go.kr/sub01_02.jsp

year college, and four-year university or higher. The occupation type has ten different categories- high officials and managers, professionals, technical engineers and semi-professionals, clerical workers, salespersons, farmers and fishers, middle-skilled technicians, low-skilled technicians, labour-intensive workers, and finally the military personnel.

Using this annual average monthly wage information from the Annual Korea Labor Statistics, we created comparison wage variables each by education, age, and occupation. We then adjusted these figures for inflation, using the regional CPI data for years 1998-2002. Finally, we took the natural logarithm of the individual and average wage variables. Other variables we newly created include hours worked per week, the union status, and a dummy for the professional and managerial types of occupation.

Our dependent variable to use is derived from the responses to a job satisfaction question with regards to wages in the KLIPS data: Respondents were asked to rate their wage satisfaction on a scale of 1 to 5, 1 being the most satisfied and 5 being the least satisfied. We recoded these answers so that 1 represents the lowest score, and 5 the highest. Since the question specifically asks about satisfaction derived from wages only, we anticipate that using this measure will make it possible to more clearly identify the own wage and comparison wage effects on job satisfaction. Table 8 summarizes new variables to be used for the estimation of our wage satisfaction equations. After dropping nine records with missing wage satisfaction information and further nineteen records with missing hours worked last week, we were left with a final sample consisting of 10,556 observations. With this sample of working individuals, we first estimated the wage satisfaction equation with explanatory variables similar to those included in our previous life satisfaction equations. Our basic regression results are reported in Table 9.

b. Estimation Results

According to the parameter estimates in Table 9, many variables previously found to affect life satisfaction do not seem to have significant effects on wage satisfaction. This is an expected result, since the dependent variable only measures satisfaction derived from wages, not other aspects of the job. Nevertheless, we included many personal background variables in order to fully control for the observed individual heterogeneity that might be correlated with the

Table 8- Summary of new variables created

Variable	*Description*	*No. Observed*	*Mean*
JobSat_Wage	Job Satisfaction in terms of wages, on a scale from 1 to 5, with 5 representing the highest level of satisfaction	10,556	2.65
professional	Dummy- 1 if occupation is professional or managerial	10,556	0.23
Union	Dummy- 1 if a union member	10,556	0.14
hour_worked	Number of hours worked last week	10,556	51.6
ln_Wage	Natural log of own wage	10,556	6.88
ln_Comp_Wage_edu	Natural log of average wage in the same educational group	10,556	7.11
ln_Comp_Wage_age	Natural log of average wage in the same age group	10,556	7.18
ln_Comp_Wage_occup	Natural log of average wage in the same occupational group	10,506	7.06

wage variable. Moreover, it would also be possible that the wage satisfaction score reflects other aspects of the job. For example, individuals generally dissatisfied with their working environment might report low scores of job satisfaction in all aspects that include wages.

Dissatisfaction in one aspect of the job can spill over to other aspects. Hence, we included a full set of personal background controls in our regressions. Several findings in Table 9 are worth to mention. First, females in general report higher wage satisfaction levels than males do. The OLS coefficient is as large as 0.38 on a 5 point scale. What this means is that females on average report wage satisfaction scores to be 0.38 point higher than males, even when the wage and other personal characteristics are controlled for. Second, wage satisfaction is "U-shaped" in age. This concurs with our previous finding from the life-satisfaction equation estimations when pooled-OLS or ordered probit were used. Third, the union status does not affect individuals' wage satisfaction responses. Fourth, homeowners are generally more satisfied with wages than those who are not. The reason we can think of is that homeowners enjoy a higher level of financial security, which would make them more content with the wages they are paid. Fifth, the number of weekly hours worked affects wage satisfaction in a negative way, but its effect is small. Sixth, neither the marital status nor the level of education affects the dependent variable. Finally, a 100% increase in the individual's own monthly wage would on average raise the satisfaction score by 0.63 point on a 5-point scale on average. The OLS estimate suggests that the monthly pay would have to rise by about 160% to move up one spot on the 5-point wage satisfaction scale.

Table 9

Parameter Estimates for the Wage Satisfaction Equation

No. Observation:10,556 Years pooled 1998-2002

Explanatory Variables	*Ordered Probit*	*OLS*
Female	0.550	0.382
	(0.028)**	(0.019)**
Age	-0.075	-0.052
	(0.009)**	(0.006)**
age_squared	0.001	(-0.001)
	(0.000)**	(0.000)**
protestant	0.081	0.056
	(0.030)**	(0.021)**
Catholic	0.057	0.041
	(-0.045)	(-0.031)
Buddhist	-0.014	-0.010
	(-0.027)	(-0.019)
other_religion	-0.022	-0.011
	(-0.079)	(-0.055)
professional	0.019	0.015
	(-0.030)	(-0.021)
Union	0.045	0.034
	(-0.032)	(-0.022)
Married	-0.039	-0.028
	(-0.048)	(-0.033)
Divorced	-0.069	-0.046
	(-0.114)	(-0.077)
Separated	-0.062	-0.045
	(-0.143)	(-0.098)
Widowed	-0.149	-0.107
	(0.088)+	(0.061)+
num_hhd	0.009	0.007
	(-0.01)	(-0.007)
Num_Child_pre	-0.014	-0.008
	(-0.024)	(-0.017)
Num_Child_old	-0.024	-0.017
	(-0.016)	(-0.011)
homeowner	0.063	0.042
	(0.024)**	(0.016)*
hours_worked	-0.007	-0.005
	(0.001)**	(0.001)**
edu_highschool	0.004	0.005
	(-0.031)	(-0.021)
edu_college	-0.061	-0.040
	(-0.045)	(-0.031)
edu_univ	0.016	0.016
	(-0.044)	(-0.03)
ln_Wage	0.916	0.634
	(0.030)**	(0.019)**

Table 9- Continued		
Explanatory Variables	*Ordered Probit*	*OLS*
Constant		-0.937 (0.162)**
(Pseudo) R-squared	0.08	0.19

Heteroscedacity-robust standard errors are in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

Notes:

1) In addition to the explanatory variables listed above, 15 region dummies and 4 time dummies are also included in both regressions.

2) Cut points (standard errors) of the ordered probit estimation are: 3.51 (.24), 5.01 (.24), 6.35 (.25), 7.90 (.25)

We now re-experiment the same wage satisfaction equation with three different additional variables- ln_Comp_Wage_edu, ln_Comp_Wage_age, and ln_Comp_Wage_occup. Since the parameter estimates for non-wage variables were virtually unchanged, we only report the coefficients on the wage variables. The results are shown in Table 10.

Let us first look at the first and the second columns of Table 10, which examine the effect of the average wage changes in the same educational group and in the same age group. Controlling for the individuals' own monthly wages, neither variable has a significant effect on wage satisfaction. The coefficient on the own wage variable is unaffected by the inclusion of the either variable. However, as shown in the third column of the table, the average wage in the same occupational group has a negative and significant effect. The OLS estimate suggests that a 100% increase in the average wage rate in the same occupation would decrease one's wage satisfaction by 0.2 point. The effect of the individual's own wage rate is about 3.3 times higher with a coefficient of 0.65. Thus, the comparison effect is again confirmed. Moreover, it is found that the reference group that has the strongest influence on the individual's wage satisfaction is the one composed of people in the same occupation. Neither the same educational group nor the same age group alone qualifies as a reference group for comparison. The result in the fourth column, which uses all three comparison wage variables, again leads to the same conclusion. Only the average wage in the same occupation matters. Therefore, based on this evidence, we argue that, as far as employees are concerned, the negative effect of comparison wage comes mostly from the pay rate changes in the same or similar occupation group.

Table 10- Reference Group Test
Parameter Estimates for the Wage Satisfaction Equation Years pooled 1998-2002

Explanatory Variables	*(1) Ordered Probit*	*(1) OLS*	*(2) Ordered Probit*	*(2) OLS*	*(3) Ordered Probit*	*(3) OLS*	*(4) Ordered Probit*	*(4) OLS*	*(5) Fixed-effects*
ln_Wage	0.917	0.634	0.918	0.635	0.938	0.648	0.916	0.634	0.599
	(0.030)**	(0.019)**	(0.030)**	(0.019)**	(0.031)**	(0.020)**	(0.030)**	(0.019)**	(0.020)**
ln_Comp_Wage_edu	0.506	0.397					0.552	0.420	
	(1.265)	(0.878)					(1.259)	(0.875)	
ln_Comp_Wage_age			0.191	0.144			0.205	0.151	
			(0.184)	(0.128)			(0.186)	(0.129)	
ln_Comp_Wage_occup					**-0.286**	**-0.195**	**-0.264**	**-0.180**	**0.195**
					(0.080)**	**(0.055)****	**(0.080)****	**(0.055)****	**(0.124)**
(Pseudo) R-squared	0.08	0.19	0.08	0.19	0.08	0.19	0.08	0.19	0.05
No. Observations	10,556	10,556	10,556	10,556	10,556	10,556	10,506	10,506	10,506
_cut1	6.984		4.509		1.769		6.615		
_cut2	8.483		6.009		3.266		8.112		
_cut3	9.826		7.351		4.604		9.451		
_cut4	11.374		8.900		6.151		10.998		

Heteroscedacity-robust standard errors are in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

Notes:
All non-income related explanatory variables listed in Table 2.10 are also included in these regressions, including region and time dummies.

Lastly, for a final check, we ran a standard fixed-effects regression using the same set of explanatory variables as the third column. The result is shown in the last column of Table 10. The fixed-effects estimated coefficient on the individual's own wage rate is about 0.6, not significantly different from our previous estimates. However, now the comparison wage variable's coefficient becomes positive and insignificant. The reason for this discrepancy in the comparison income effects found in the pooled-OLS and the fixed-effects models is not clear. Whether this discrepancy comes from the measurement errors, the short time period of the sample, or the individual fixed effects cannot be said. Perhaps, the annual increases in the industry salaries (in real terms) are so small that the mere five years of data are not enough to identify the true effect. In this case, only using longer-run panel data would help better identify the comparison income effect on wage satisfaction. Hence, this finding calls for further research in this area. More studies comparing the cross-sectional and longitudinal estimation results should follow in order to confirm the negative effect of comparison wages and the reference group on subjective well-being.

IV. Conclusion

In this paper, we have thoroughly examined the determinants of subjective well-being, using the responses to a set of life satisfaction questions found in the Korean Labor Income Panel Study. Both our pooled-OLS and ordered probit estimation results suggest that the incidence of unemployment, divorce, and separation negatively and significantly affects the life satisfaction levels of individuals. Of theses, separation has the largest effect on well-being. It is found that the negative effect of separation is a lot greater than that of divorce on average. By contrast, the widowed are happier than singles, but unhappier than the married, holding other factors constant.

In addition, homeownership has a large and positive impact on individual well-being in Korea, reflecting the growing concerns over high real estate prices in the country. The recent measures taken by the government in 2005 to cool down the rising real estate prices should thus be viewed as an appropriate policy from the subjective welfare's stand point. Moreover, the positive and significant coefficients on the education dummies show that people with more years of education derive extra satisfaction from a rise in status or others' positive perception towards them, independently of income.

The huge negative effects of unemployment and separation are also confirmed in our fixed-effects estimation results. So are the positive effects of marriage, homeownership, and the student status. However, the fixed effects-estimated income effect turns out to be a lot smaller in size than the pooled estimate. One way to interpret this reduction in the coefficient on income is to view it as a supporting evidence for Easterlin's (2001) hypothesis that individual happiness does not change much over time as income increases due to rising aspirations, but the initial gap between the poor and rich remains large, as is observed in cross-sections. Another explanation for this discrepancy can be that there are unobservables positively correlated with individual life satisfaction which are also positively correlated with income. Since our fixed-effects estimation controls for these time-invariant unobservables, the coefficient is now smaller, capturing only the pure income effect, independent of the effect of unobservables. Regardless of which explanation is correct, the fixed-effects estimation results should be more reliable than the pooled results in a sense that the differencing controls for time-invariant unobservables and the method does not rely on the assumption of the dependent variable's interpersonal comparability.

Our monetary evaluation of the psychological cost of separation and divorce based on our fixed effects results stands at about KRW 172 million in annual family income. This figure is surprisingly close to the average amount of alimony the divorced women in Korea actually wanted, as reported by another survey. But in fact these women were paid only about KRW 49.6 million on average. Thus, our calculation suggests that the average amount of alimony claimed by divorced women is in line with their utility loss evaluated in terms of income. Moreover, we conclude from this evidence that the current level of alimony actually paid to them is too low for their psychological pain to be fully compensated for.

Our next attempt was to test the effect of comparison income, utilizing the average household income data by region and household size from another national survey. We find that the comparison income does matter to one's income satisfaction - others' performance negatively affects my welfare relating to income. The effect, however, is much smaller than that of own income in size and does not turn out to be statistically significant in the overall life satisfaction equation.

Finally, our reference group tests for employees reveal that the group that has the strongest influence on the individual's wage satisfaction is the one composed of people in the same or similar occupation. Neither the same educational group nor the same age group alone qualifies as a reference group for comparison. Thus, our finding suggests that, as far as employees are concerned, the negative effect of comparison wage comes mostly from the pay rate changes in the same or similar occupation group. The results from our fixed-effects estimation, however, do not support this. The effect of comparison wage disappears when examining the changes in wage and wage satisfaction variables of the same individuals. We suspect that the annual increases in the industry salaries (in real terms) are so small that the mere five years of data are not enough to identify the true effect. Hence, this mixed result calls for further research using a richer and longer-run panel dataset in order to confirm the comparison effect for employees.

Subjective well-being has only recently begun to become a hot topic in economics. As the ultimate goal of any economic policy should be to increase human happiness or aggregate utility of the society, happiness research can provide an important ground for policy decisions at the macro level. Undoubtedly, economic policies written without fully understanding what factors make people happier can be misdirected. Economics should aim to provide a clear picture of what makes people happy, beyond individual income. We hope that our work has provided the foundation for additional advancements in this arena.

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