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STATE DEPENDENCE, UNOBSERVED HETEROGENEITY, AND HEALTH DYNAMICS IN KOREA*

YONG-WOO LEE

School of Economics and Finance, Yeungnam University
Gyeongbuk 712-749, Korea
leastsquares@yu.ac.kr

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Abstract

This paper investigates the determinants of individual health and its dynamics using the Korea Labor and Income Panel Study. The paper examines how state dependence, unobserved heterogeneity, and observed heterogeneity jointly affect overall health evolution. For this, a dynamic random effects ordered probit model with a simple solution to the initial conditions problem is estimated and the estimation results show that health dynamics in Korea are characterized by significant positive state dependence and unobserved heterogeneity. The explanatory power of many socioeconomic variables disappears if state dependence and unobserved heterogeneity are controlled for. Two robustness checks with respect to attrition bias and reporting reliability further validate these empirical results.

Keywords: self-assessed health, dynamic random effects ordered probit model, state dependence
JEL Classification Codes: I1, C25

I. *Introduction*

Self-assessed health (SAH) has been one of the most frequently used measurement for analyzing individual health. Although it is a simple categorical variable and assessed by survey respondents in a subjective manner, SAH has been found to be a powerful indicator of mortality, morbidity, and medical care use according to previous research (e.g., Idler and Benyamini, 1997). Furthermore, it is easy to collect and can be used to perform comparative studies across countries because most countries collect it (Subramanian *et al*., 2010).[1] The main objective of this paper is to investigate the dynamics of individual health measured by SAH over time in Korea. Analyzing the dynamics of individuals' health status entails the

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[1] It should be noted that a cross-country comparison of the SAH may be difficult because of reporting heterogeneity across regions and countries. King *et al*. (2004) pioneer the use of anchoring vignettes to correct for reporting heterogeneity. However, this method also has some limitations as shown in d'Uva *et al*. (2011).

identification of true state dependence in the persistence of the health status. Previous studies have shown a tendency of persistence in health evolution in the sense that current health is a significant determinant of the future health status. However, this persistence does not necessarily represent the genuine probabilistic feature of health dynamics, and, therefore, unobserved as well as observed heterogeneity should be carefully controlled for to correctly identify how health in the next period is accounted for by current health. According to Heckman (1981c), the improper treatment of unobserved heterogeneity gives rise to a conditional relationship between current and future experiences, which is referred to as spurious state dependence. To distinguish between true and spurious state dependence is of considerable interest in policy-making. For example, if there exists true state dependence in health evolution, then short-term health policies that intervene in individual health tend to improve individual health in the long term. As a result, preventive medicine can then play an important role in enhancing individual health. On the other hand, if unobserved heterogeneity is correlated over time and not properly controlled for, then the past health status may appear to be a determinant of future health, solely because it is a proxy for such temporally persistent unmeasured variables. In this case, short-term health policies have no effect on the longer-term health status. However, despite its relative importance, few studies have examined the dynamics of health, although many have focused on the dynamics of labor income and labor income variability in labor economics. Contoyannis *et al*. (2004) are the first to take into account the importance of state dependence and unobserved heterogeneity by using British Household Panel Survey (BHPS) for the 1991-1998 period and find the existence of state dependence in health. Further, they explicitly address two fundamental problems: the initial conditions problem arising from the estimation of dynamic panel data models and attrition bias from longitudinal non-responses ("suvivorship bias"). They tackle these problems by using the so-called "Wooldridge solution" (Wooldridge, 2005) and the inverse probability weighted estimation method (Wooldridge, 2002b). Halliday (2008) investigates the evolution of health by allowing for unobserved heterogeneity and state dependence through the Panel Study of Income Dynamics (PSID) for the 1984-1997 period and finds evidence of state dependence, concluding that individual characteristics that trace back to early adulthood and before can have far reaching effects on health. Ayllón and Blanco-Perez (2012) examine health dynamics in Spain by using the Spanish component of the European Community Household Panel (ECHP). In addition to the methods proposed in Contoyannis *et al*. (2004), they implement a Heckman selection model with an initial conditions equation as an ordered probit. Vaillant and Wolff (2012) explore health dynamics by using the Living Standard Measurement Study (LSMS) in Albania collected by the World Bank in 2002, 2003 and 2004. Because the data have only three waves, they do not explore dynamic aspects, as in the aforementioned papers, and thus, estimate a random effects probit model and implement variance decomposition method. They find evidence of strong state dependence in health in Albania. Heiss (2011) also finds the previous health to be a significant predictor of future health by using the first seven waves of the Health and Retirement Study (HRS). Further, he proposes a joint model with an autocorrelated latent health component in both SAH and mortality instead of using models with random effects and state dependence.

The present paper is the first to investigate the level of genuine state dependence in the individual health status in Korea, one of the leading economies in East Asia. Using the Korea Labor and Income Panel Study (KLIPS), the paper closely follows the methods in Contoyannis *et al*. (2004) and Ayllón and Blanco-Perez (2012) and explicitly controls for ubobserved as well as observed heterogeneity to identify genuine state dependence, as suggested in previous studies. However, unlike in previous studies since Contoyannis *et al*. (2004), which have long used conventional methods, this paper uses a state-of-the-art method to cope with the initial conditions problem. In implementing the Wooldridge solution, many researchers have used initial dependent variables and within-means of explanatory variables to specify an auxiliary model for the conditional distribution of unobserved heterogeneity. This is in fact different from the original Wooldridge solution, in which initial dependent variables and time-varying explanatory variables at each period are used. Rabe-Hesketh and Skrondal (2013) show that the popular conventional version can yield a severe bias and instead propose an alternative method using initial dependent variables, initial explanatory variables and within-means of explanatory variables omitting initial values. The present paper follows this methodology.

In addition to investigating health dynamics, the paper performs two robustness checks to vaildate the results. First, simple variable addition tests proposed in Verbeek and Nijman (1992) are conducted to detect the presence of attrition bias, and then the baseline model augmented with inverse probability weights is estimated to compare the estimation results with those results from the baseline model to determine whether attrition bias has a significant effect on estimated coefficients of interest. Second, the reliability of reporting SAH by respondents is evaluated. The question here is whether there is a significant measurement error when respondents self-assess their own health. This is an important empirical question because of the widespread use of SAH in empirical health economics. There have been two methods to test the reliability of reports. One way is to examine the accuracy of SAH by comparing SAH with objective health measures (Johnston *et al*., 2009; Suziedelyte and Johar, 2013). The other method tests the validity of self-reports by comparing actual changes in SAH over two consecutive periods with retrospective answers (Crossley and Kennedy, 2002; Vaillant and Wolff, 2012). The present paper adopts the latter approach. Crossley and Kennedy (2002) analyze the 1995 Australian National Health Survey, which includes a random sub-sample of respondents answering a standard SAH question twice - before and after an additional set of health-related questions. They find 28% of all respondents to change their reported health status suggesting the presence of a considerable measurement error. Vaillant and Wolff (2012) extend Crossley and Kennedy's method to dynamic context by using the Albanian data set mentioned earlier. The Albanian data set has retrospective SAH question for which the respondent should answer regarding whether his or her health is better, more or less the same, or worse in comparison to that in the the previous period. They examine whether the answers for this retrospective question are compatible with those for SAH over two consecutive years in terms of reporting consistency and find sufficient reporting consistency, which is in contrast to the findings of Crossley and Kennedy (2002). The present paper follows the approach in Vaillant and Wolff (2012).

The rest of this paper is organized as follows: Section 2 describes the KLIPS data set and variables used in the estimation and presents various aspects of SAH in Korea. Section 3 explains the empirical models and highlights issues regarding empirical procedures. Section 4 presents and discusses the estimation results. Section 5 performs robustness checks, and section 6 concludes.

II. *The KLIPS Data Set*

1. The Sample and Variables

The analysis is based on micro data from KLIPS for the years 2003-2012. KLIPS is Korea's largest and longest-running annual longitudinal survey of households and individuals residing in urban areas. It is conducted annually to track characteristics of households as well as individuals' economic activities, labor movement, income, expenditures, education, job training, and social activities. Since the fourth wave in 2003, it has also recorded individual health variables such as SAH, various forms of morbidity and the use of medical care. KLIPS was initiated by the Korea Labor Institute in 1998, and the most recently released data set is the 15th wave in 2012. The original sample of KLIPS includes 5, 000 households recruited through two stage stratified clustering sampling. The sample considered in this paper is composed of individuals over 15 years of age. The analysis uses both balanced and unbalanced samples. The unbalanced sample includes only those who are observed at the initial period of the sample (i.e., the year 2003). Initially, there are 115,573 observations for 16,873 individuals. For the data, those whose information on age, SAH, and education is missing are excluded. This procedure produces 115, 494 observations for 16, 866 individuals. From this, balanced samples are constructed. For the unbalanced sample, those individuals who are not observed during the initial sample period are excluded, and this cleaning procedure produces a working sample of 5,633 individuals, 56,330 individual-wave observations for the balanced sample, and 11,484 individuals and 91,065 individual-wave observations for the unbalanced sample.

Individual health is measured by the SAH indicator incorporating individual perceptions of health in various dimensions such as physical, mental, and socio-economic factors. SAH is recorded by the response to the question "how is your health as a whole?". The respondent chooses one out of five categorical answers: 'excellent' (1), 'good' (2), 'fair' (3), 'poor' (4), or 'very poor' (5).

As the main explanatory variables, age is included as a fourth-order polynomial (age, age2 $= age^2/100$, age3 $= age^3/10,000$, age4 $= age^4/1,000,000$), the categorical marital status (single, married, divorce/separation, and widow/widower), the number of children of different ages (nch0004, nch0511, and nch1218), the number of individuals in the household, categorical educational qualifications (less than middle school, high school, college, more than college), the categorical work status (workers with permanent contracts, workers with temporary contracts, employers/self-employed, supporting family businesses without being paid, economically non-active, and unemployed), and the logarithm of equivalized and CPI-deflated annual household income.[2] Descriptive statisitcs are shown in Table 1 for the pooled unbalanced sample.

[2] According to the ONS, equivalisation is a standard methodology that adjusts household income to account for different demands on resources by considering the size and composition of households. See Office for National Statistics (2014) for comprehensive information on how to calculate equivalised income.

Table 1 Descriptive Statistics—Pooled Unbalanced Samples

variable	mean	standard deviation	note
h	2.629	0.876	self-assessed health
age	46.85	16.56	
gen2	0.529	0.499	female
dms1	0.200	0.400	marital status is single
dms3	0.035	0.185	marital status is divorced/separated
dms4	0.091	0.288	marital status is widowed
			(reference group is married)
nch0004	0.125	0.391	number of children in household aged 0-4
nch0511	0.249	0.574	number of children in household aged 5-11
nch1218	0.306	0.632	number of children in household aged 12-18
nhh	3.413	2.176	number of household members
middleschool	0.356	0.379	maximum level of education is middle school
college	0.096	0.294	maximum level of education is college
university	0.173	0.378	maximum level of education is university
			(reference group is high school education)
tcwork	0.093	0.291	worker with temporary contract
employer	0.152	0.359	employer or self-employed
family	0.040	0.196	family business without being paid
ena	0.408	0.492	economically non-active
unemp	0.013	0.112	unemployed
			(reference group is worker with permanent contract)
log(income)	7.221	1.036	logarithm of equivalized annual household income

2. Self-Assessed Health in Korea

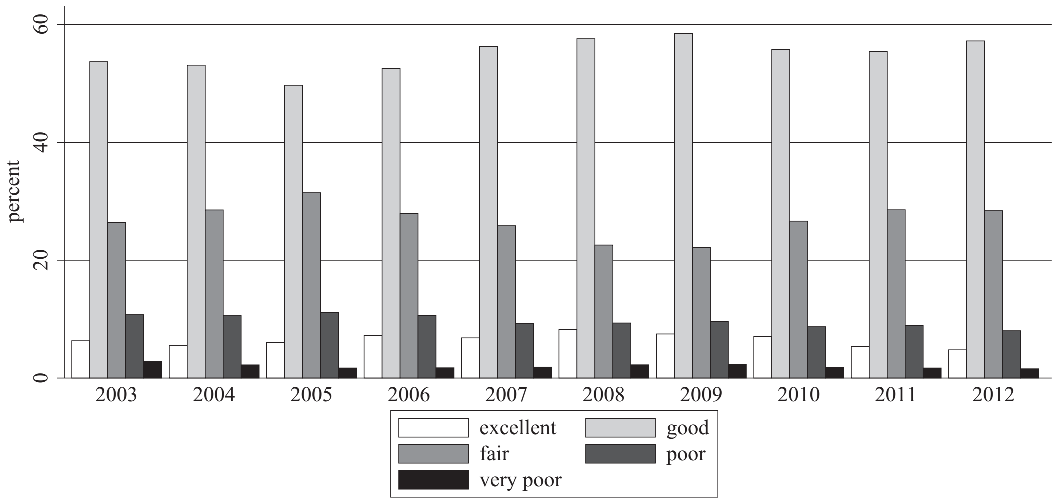
This subsection presents the evolution of SAH in Korea by using the samples described in the previous subsection. Figure 1 presents the distribution of SAH across all panel waves. A majority of observations are in either good or fair health during the sample period (about 80% and 77% for men and women, respective).[3] Further, mean SAH slightly improves, with 87.51% of all respondents answering a positive health status (excellent, good, or fair) in 2012, whereas 82.55% stating so in 2003. Figure 2 shows the age profile of SAH, which exhibits natural degeneracy in health as individuals age. Figure 3 describes the distribution of SAH by quintiles of equivalized real household income. This shows that the distribution of SAH improves with an increase in household income. That is, the respondents in the lower income quintile are likely to report a poorer health status, whereas those in the higher income quintiles, a better health status. Figure 4 displays the relationship between the maximum educational attainment and SAH. There is a positive gradient between them, meaning that the respondents with higher educational qualifications tend to report a better health status. This is why the educational status is considered as a major determinant of health, as suggested in Contoyannis *et al*. (2004).[4]

[3] In fact, this is slightly different from that of other countries'. For instance, a majority of respondents answered being in either excellent or good health in the HRS, the BHPS and the Spanish component of the ECHP.

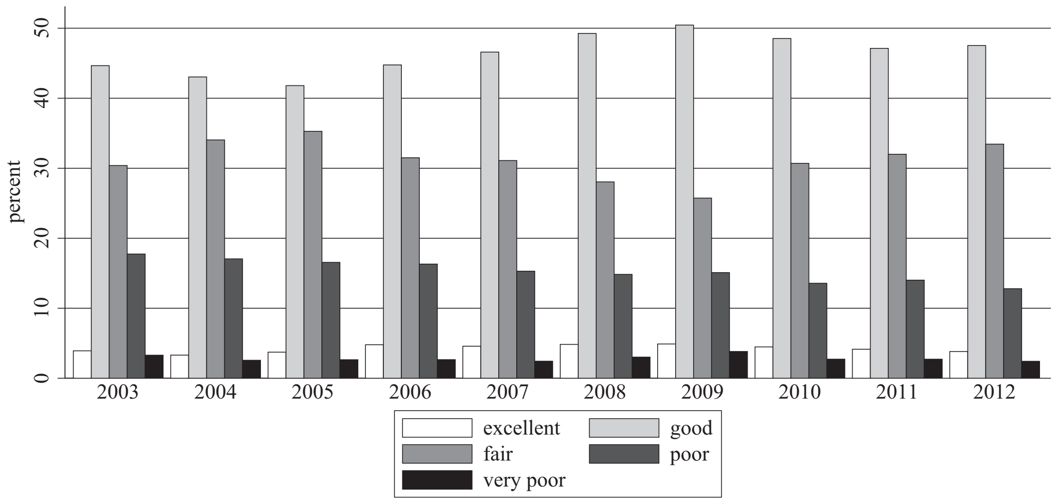
[4] In addition, Feldstein (2005) states that years of education in a household may be a proxy for greater awareness of the need for medical care, for different attitudes toward seeking care, and for greater efficiency in its purchase and production. (Feldstein, 2005, p.92)

Fig. 1 Self-assessed Health Status by Wave

(a) Men



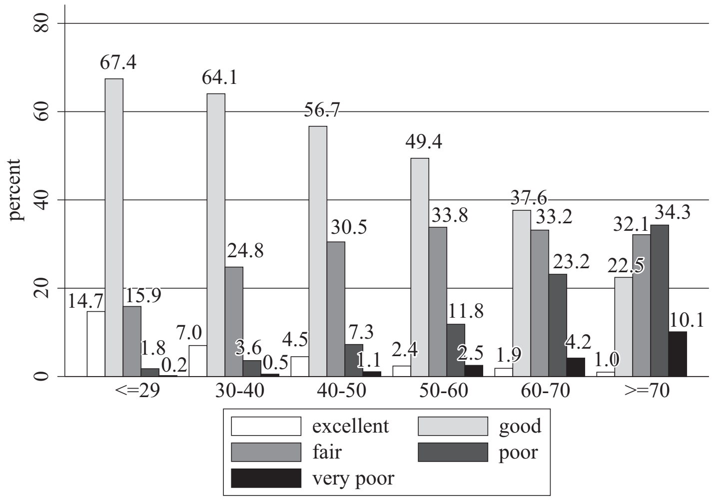
(b) Women



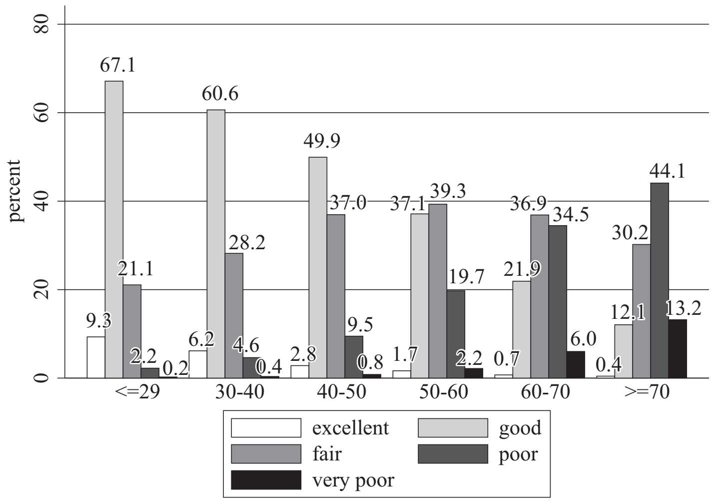
Finally, Tables 2 and 3 show transition matrices of health status transitions between $t-1$ and t. It is clearly seen from these tables that persistence in health outcomes is apparent. That is, individuals are more likely to remain close to their previous health state than move away from it. For instance, for men, 69.56% of those reporting good health in $t-1$ stated the same health status in t, with 46.07% reporting a poor health. The same qualitative features apply to the

Fig. 2 Self-assessed Health Status by Age Group

(a) Men



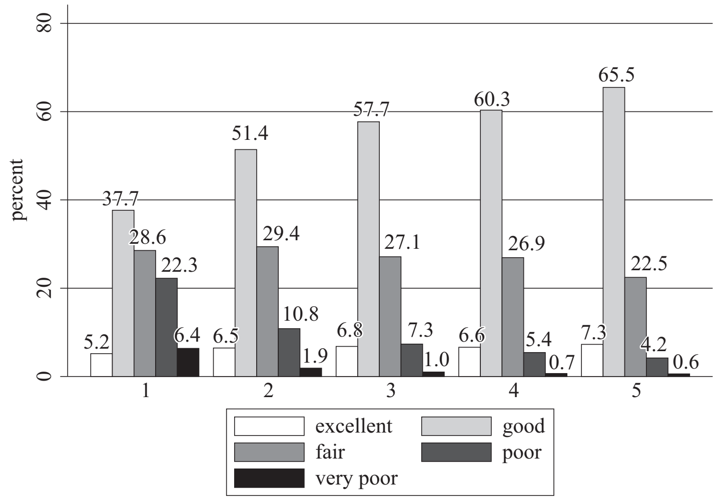
(b) Women



female sample. Overall, this implies that there is a certain degree of state dependence in the evolution of individual health. The health dynamics shown here provide mere descriptions without any formal modeling. Now health dynamics are examined based on a formal empirical model that controls for unobserved factors and is conditional on other explanatory variables.

FIG. 3 SELF-ASSESSED HEALTH STATUS BY QUINTILE OF INCOME

(a) MEN



(b) WOMEN

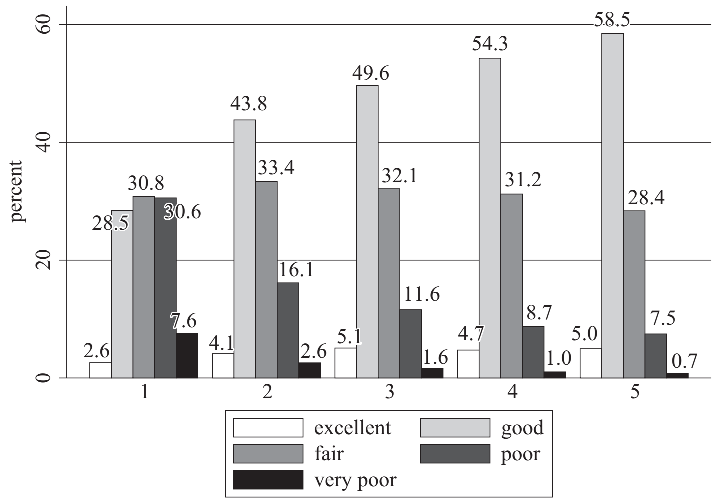
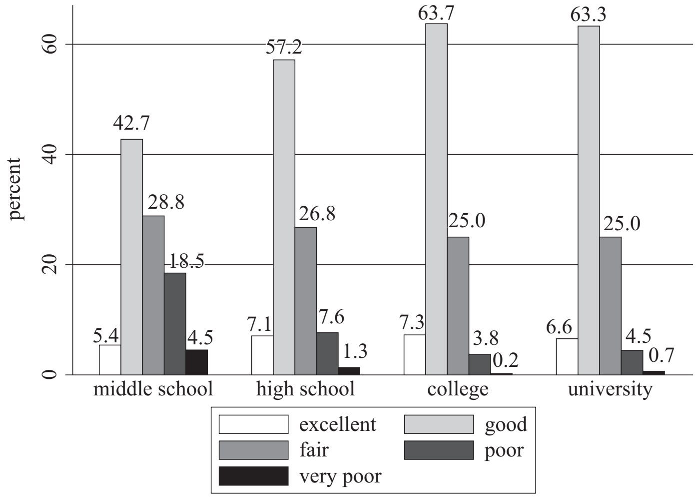


Fig. 4 Self-assessed Health Status by Educational Attainment

(a) Men



(b) Women

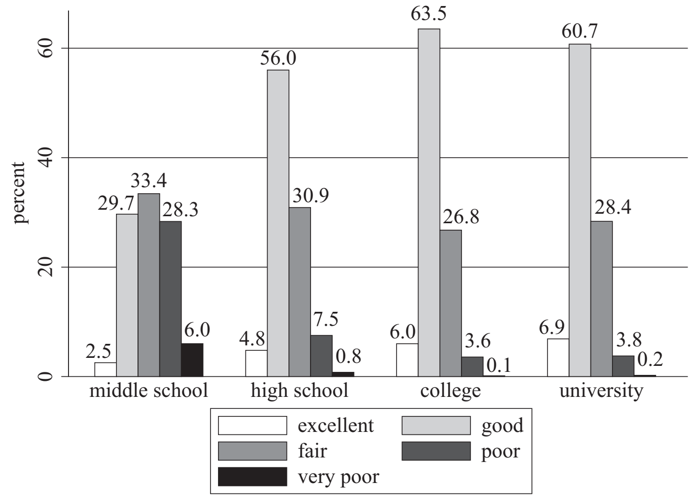


TABLE 2 SELF-ASSESSED HEALTH TRANSITIONS BETWEEN $t-1$ AND t (MEN)

	EX	GOOD	FAIR	POOR	VERY POOR
EX	31.61	55.49	10.70	2.08	0.13
GOOD	5.68	69.56	21.74	3.34	0.29
FAIR	2.80	41.82	44.78	9.60	0.99
POOR	0.92	17.21	27.77	46.07	8.03
VERY POOR	0.23	5.63	8.56	44.78	40.80

TABLE 3 SELF-ASSESSED HEALTH TRANSITIONS BETWEEN $t-1$ AND t (WOMEN)

	EX	GOOD	FAIR	POOR	VERY POOR
EX	30.24	54.11	12.97	2.62	0.05
GOOD	4.41	67.21	23.76	4.31	0.32
FAIR	1.89	34.84	48.54	13.56	1.17
POOR	0.60	12.15	29.23	50.10	7.92
VERY POOR	0.00	3.40	9.20	47.14	40.26

III. *Models and Estimation Methods*

1. Dynamic Ordered Probit

To model the dynamics of SAH in Korea described in the previous section, the dynamic panel ordered probit specifications in Contoyannis *et al*. (2004) and Ayllón and Blanco- Perez (2012) are used. We estimate on both balanced and unbalanced samples. Given this specification, the latent health model framework can be written as

$$h_{it}^{*}=\beta' x_{it}+\gamma' h_{it-1}+\alpha_i+\epsilon_{it}\ (i=1,\ ...,\ N;t=2,\ ...,\ T_i) \tag{1}$$

This model consists of three components. First, h_{it-1} is an indicator of the individual health status measured by SAH in the previous wave, and γ are the parameters to be estimated that capture state dependence. That is, if $\gamma\neq0$, then the outcome h_{it-1} influences outcome in the following period t. Second, α_i is an individual-specific and time-invariant random component[5] assumed to follow a standard normal distribution with mean zero and variance σ_α^2. This component represents individual unobserved heterogeneity and is correlated with h_{it-1}. Modeling unobserved heterogeneity is important to avoid spurious state dependence. As Heckman (1981b) and Heckman (1981c) explain, if individual differences are correlated over time, and if these differences are not properly controlled for, then previous health may appear to be a determinant of future health solely because it is a proxy for temporally persistent unobservable variables. Third, x_{it} is a set of observed explanatory variables that are strictly exogenous and β captures observed heterogeneity. Further, ϵ_{it} is a serially independent error

[5] A fixed effects model is not considered because of the incidental parameter problem. Unlike in the linear case, the standard estimation of α_i such as maximum likelihood estimation along with other parameters to be estimated leads to the inconsistent estimation of not only α but also other parameters, that is, β and γ, with T fixed and $N\rightarrow\infty$. The reader is referred to Lancaster (2000) for further details.

term assumed to follow a standard normal distribution with zero mean and unit variance. It is further assumed that ϵ_{it} is uncorrelated with α_i and x_{it} are uncorrelated with ϵ_{it} for all t and s.

Given that h^*_{it} is an unobservable latent variable, only the category chosen by the individual at each point in time can be observed. The observation mechanism is represented by

$$h_{it}=k \text{ if } \kappa_{k-1}<h^*_{it}\leq\kappa_k,\ k=1,\ ...,\ K \tag{2}$$

where κ_0 is taken as $-\infty$, $\kappa_k\leq\kappa_{k+1}$, and κ_k is taken as $+\infty$. K is the number of all possible outcomes. Given the assumption that the error term is normally distributed, the probability of observing the particular outcome k for response h_{it} can be derived as

$$\begin{aligned} p_{itk}\equiv Pr(h_{it}=k|\boldsymbol{\kappa},\ x_{it},\ h_{it-1},\ \alpha_i)&=Pr(\kappa_{k-1}<\beta' x_{it}+\gamma' h_{it-1}+\alpha_i+\epsilon_{it}\leq\kappa_k)\\ &=Pr(\kappa_{k-1}-\beta' x_{it}-\gamma' h_{it-1}-\alpha_i<\epsilon_{it}\leq\kappa_k-\beta' x_{it}-\gamma' h_{it-1}-\alpha_i)\\ &=\Phi(\kappa_k-\beta' x_{it}-\gamma' h_{it-1}-\alpha_i)-\Phi(\kappa_{k-1}-\beta' x_{it}-\gamma' h_{it-1}-\alpha_i), \end{aligned}$$

where $\boldsymbol{\kappa}$ is a set of cutpoints, κ_1, κ_2, , , κ_{K-1} and $\Phi(\cdot)$ is the standard normal distribution. Here, x_{it} does not contain a constant term because its effect is absorbed into cutpoints.

To implement the random effects estimator the unobserved heterogeneity term is integrated out, giving the sample log-likelihood function l as follows.

$$l=\sum_{i=1}^{n}\{\ln\int_{-\infty}^{+\infty}\exp(-\alpha^2/2\sigma^2_\alpha)(1/\sqrt{2\pi\sigma^2_\alpha})[\prod_{t=1}^{T_i}p_{itk}]d\alpha\} \tag{3}$$

The integral can be approximated with the M-point Gauss-Hermite quadrature.[6]

2. Initial Conditions Problem

As can be seen in (3), α needs to be integrated out of the distribution to estimate the model, and this raises the issue of how initial observations, h_{i1} can be treated. One possibility is to assume that h_{i1} is actually independent of α_i. In this case, α_i can be integrated out in the usual fashion. However, this is not valid if the first observation is not the true initial outcome of the process, which is the case in this analysis.[7] More realistically, if correlations between h_{i1} and α_i are allowed, then there arises an endogeneity problem. That is, in the conditional density of h_{i1}, the regressor h_{i1} is correlated with the unobserved random effect. This is usually called the initial conditions problem.[8] Two main approaches have been proposed to handle this problem. Heckman (1981a) proposes dealing with the conditional density of h_{i1} by adding an equation that explicitly models the dependence of h_{i1} on α_i and $x_i=\{x_{i2}, x_{i3}, ..., x_{iT}\}$.[9] An alternative approach that is much easier to implement than the Heckman estimator has been suggested in Wooldridge (2005). This approach suggests specifying an auxiliary model for the

[6] Ordered probit models are estimated using both pooled ordered probit and random effects ordered probit specifications. These models are estimated using STATA version 13 with oprobit and xtoprobit, respectively.

[7] Wooldridge (2005) points out that even when the econometrician has access to the whole process history, the problem remains unresolved.

[8] The reader is referred to Wooldridge (2002a) and Wooldridge (2005) for the more formal treatment of the initial conditions problem.

[9] This approach is not available in standard software.

conditional distribution of unobserved effects by conditioning on the initial dependent variable and explanatory variables. That is,

$$\alpha_i = \alpha_0 + \alpha_1' h_{i1} + \alpha_2' x_1 + u_i, \text{ where } u_i \sim \mathrm{N}(0, \sigma_u^2) \tag{4}$$

Note that this method is very similar in spirit to the methods proposed in Mundlak (1978) and Chamberlain (1980), who parameterize individual effects to allow for possible correlations between explanatory variables and individual effects. While original Wooldridge solutions include values of time-varying explanatory variables at each period except for the initial period, a more common specification includes the within-means of time-varying explanatory variables, that is, using $\bar{x}_i = (\sum_{t=1}^{T} x_{it})/T$ instead of x_i in (4), without any solid justification in the literature (e.g., Contoyannis *et al*., 2004; Michaud and Tatsiramos, 2011; Ayllón and Blanco-Perez, 2012). This may be because it is parsimonious. However, Rabe-Hesketh and Skrondal (2013) shows that the auxiliary model is overly constrained if it includes within-means of time-varying explanatory variables across all periods including the initial period. This paper takes account of this argument and implements one of the suggested alternatives:

$$\alpha_i = \alpha_0 + \alpha_1' h_{i1} + \alpha_2' \bar{x}_i^{+} + \alpha_3' x_{i1} + u_i, \text{ where } \bar{x}_i^{+} = (\sum_{t=2}^{T} x_{it})/(T-1) \tag{5}$$

That is, the constraint is relaxed by omitting the initial period explanatory variables from within-means. Substituting equation (5) into equation (1) gives the standard random effects structure because u_i is not correlated with x_i and h_{i1}. This is the empirical model estimated in this study.

IV. *Empirical Results*

Tables 4 and 5 present the estimation results for ordered probit models based on pooled and random effects specifications for both balanced and unbalanced samples.[10] Estimations are performed separately for men and women. To formally test for state dependence, dynamic models including dummy variables representing one-period lags of categories of the dependent variable[11], $h_{t-1}(1) \sim h_{t-1}(5)$, are estimated. Random effects specifications introduce explicitly unobserved individual heterogeneity into the dynamic model by specifying random effects. All models parameterize unobserved individual effects as a function of within-individual means of the time-varying regressors specified in (5)[12] and a vector of dummy variables to represent first-period observations of the dependent variable, $h_1(1) \sim h_1(5)$.

As shown in rows 1−4 in Tables 4 and 5, all coefficients that account for the lagged value of SAH in Korea are clearly significant at 1%. There is a negative gradient in estimated effects from very poor to excellent previous health. That is, health shocks are not immediately

[10] As explained in Contoyannis *et al*. (2004), estimated coefficients for random effects are not directly comparable to those reported for pooled models because of different scaling methods for the variance of error terms.

[11] The baseline category is lagged good health, $h_{t-1}(2)$.

[12] Estimated coefficients for both within means and initial values of time-varying explanatory variables are not reported for a parsimonious reason. They are available from the author upon request.

adjusted, and current health depends on the past health experience. Furthermore, the results show a need to control for unobserved individual heterogeneity in analyzing health dynamics. Note that the variance of random effects is siginificant at 1%, and allowing for unobserved heterogeneity slightly improves the fit of the model, as shown in the change in the log-likelihood value. Approximately 17% for men and 22% for women of the latent error variance is attributable to unobserved heterogeneity, as measured by the intra-unit correlation coefficient

TABLE 4 DYNAMIC ORDERED PROBIT WITH WOOLDRIDGE SOLUTIONS FOR INITIAL CONDITIONS PROBLEM (MEN)

	Pooled model		Random effects	
	Balanced NT=22,401	Unbalanced NT=35,346	Balanced NT=22,401	Unbalanced NT=35,346
$h_{t-1}(1)$	−0.710***(0.043)	−0.633***(0.030)	−0.473***(0.047)	−0.421***(0.033)
$h_{t-1}(3)$	0.499***(0.018)	0.475***(0.015)	0.305***(0.021)	0.291***(0.017)
$h_{t-1}(4)$	1.079***(0.028)	1.073***(0.023)	0.674***(0.033)	0.695***(0.028)
$h_{t-1}(5)$	1.790***(0.064)	1.837***(0.050)	1.195***(0.071)	1.283***(0.056)
ln(income)	−0.007(0.011)	−0.014(0.009)	−0.013(0.012)	−0.019**(0.009)
meanln(income)	−0.187***(0.020)	−0.136***(0.015)	−0.237***(0.029)	−0.157***(0.020)
age	−0.081(0.113)	0.017(0.060)	−0.085(0.115)	0.025(0.062)
age2	0.377(0.339)	0.056(0.198)	0.415(0.345)	0.057(0.203)
age3	−0.606(0.436)	−0.199(0.273)	−0.682(0.443)	−0.234(0.279)
age4	0.328(0.202)	0.157(0.133)	0.376*(0.206)	0.191(0.136)
single	0.067(0.086)	−0.050(0.062)	0.086(0.088)	−0.048(0.064)
div/sep	0.046(0.095)	0.084(0.077)	0.067(0.097)	0.101(0.079)
widow	0.064(0.128)	0.044(0.108)	0.095(0.130)	0.065(0.110)
middleschool	0.096***(0.020)	0.114***(0.017)	0.114***(0.031)	0.145***(0.024)
college	−0.016(0.030)	−0.015(0.023)	−0.005(0.045)	−0.001(0.033)
university	−0.059***(0.023)	−0.044***(0.017)	−0.067**(0.034)	−0.041*(0.025)
hhsize	−0.014(0.017)	−0.021(0.013)	−0.013(0.017)	−0.023*(0.013)
nch0004	0.103***(0.039)	0.045(0.030)	0.123***(0.039)	0.060*(0.031)
nch0511	0.041(0.030)	0.018(0.024)	0.053*(0.031)	0.026(0.024)
nch1218	−0.0004(0.024)	0.014(0.019)	0.004(0.025)	0.020(0.020)
tcwork	−0.069(0.045)	−0.051(0.037)	−0.079*(0.046)	−0.053(0.037)
employer	0.018(0.043)	−0.041(0.036)	0.018(0.044)	−0.047(0.036)
famly	−0.056(0.118)	−0.071(0.101)	−0.028(0.120)	−0.065(0.103)
ena	0.389***(0.042)	0.241***(0.032)	0.465***(0.042)	0.297***(0.032)
unemp	−0.037(0.074)	−0.019(0.055)	−0.030**(0.075)	−0.009(0.056)
$h_1(1)$	−0.124***(0.040)	−0.164***(0.029)	−0.196***(0.060)	−0.247***(0.041)
$h_1(3)$	0.124***(0.019)	0.145***(0.015)	0.195***(0.029)	0.228***(0.022)
$h_1(4)$	0.498***(0.028)	0.474***(0.023)	0.735***(0.044)	0.699***(0.034)
$h_1(5)$	0.714***(0.062)	0.724***(0.049)	1.083***(0.097)	1.110***(0.071)
cut1	−4.085(3.077)	−0.667(0.642)	−4.773(4.722)	−0.463(0.838)
cut2	−1.786(3.077)	1.560(0.642)	−2.294(4.722)	1.938(0.838)
cut3	−0.550(3.077)	2.811(0.642)	−0.954(4.722)	3.293(0.838)
cut4	0.949(3.077)	4.249(0.642)	0.681(4.722)	4.856(0.838)
σ_u^2			0.201(0.013)	0.195(0.010)
Log likelihood	−21,317.2	−33,677.9	−21,027.1	−33,304.2

Notes: 1 Standard errors are in parentheses.
2 Levels of significance are 1%(***), 5%(**), and 10%(*), respectively.
3 Cuts 1-4 are the estimated cut points.

TABLE 5 DYNAMIC ORDERED PROBIT WITH WOOLDRIDGE SOLUTIONS FOR INITIAL CONDITIONS PROBLEM (WOMEN)

	Pooled model		Random effects	
	Balanced NT=28,296	Unbalanced NT=40,560	Balanced NT=28,296	Unbalanced NT=40,560
$h_{t-1}(1)$	−0.740***(0.044)	−0.658***(0.034)	−0.443***(0.049)	−0.391***(0.037)
$h_{t-1}(3)$	0.521***(0.017)	0.508***(0.014)	0.280***(0.019)	0.289***(0.016)
$h_{t-1}(4)$	1.118***(0.023)	1.109***(0.020)	0.592***(0.028)	0.633***(0.024)
$h_{t-1}(5)$	1.860***(0.048)	1.859***(0.040)	1.069***(0.055)	1.146***(0.046)
ln (income)	−0.008(0.010)	−0.010(0.008)	−0.012(0.010)	−0.015*(0.008)
meanln (income)	−0.177***(0.017)	−0.150***(0.013)	−0.244***(0.025)	−0.188***(0.018)
age	0.013(0.070)	0.013(0.052)	0.034(0.073)	0.035(0.054)
age2	0.028(0.221)	0.008(0.169)	−0.013(0.228)	−0.046(0.175)
age3	−0.111(0.294)	−0.067(0.227)	−0.099(0.303)	−0.023(0.234)
age4	0.082(0.139)	0.057(0.108)	0.095(0.143)	0.049(0.111)
single	0.160*(0.087)	0.178***(0.066)	0.197**(0.090)	0.210***(0.068)
div/sep	0.091(0.094)	0.088(0.077)	0.122(0.096)	0.118(0.079)
widow	0.076(0.066)	0.039(0.059)	0.113*(0.067)	0.078(0.060)
middleschool	0.163***(0.020)	0.169***(0.017)	0.212***(0.034)	0.215***(0.027)
college	−0.022(0.028)	−0.006(0.022)	−0.001(0.044)	0.014(0.033)
university	0.005(0.026)	0.007(0.020)	0.036(0.042)	0.033(0.030)
hhsize	0.009(0.015)	0.004(0.012)	0.012(0.015)	0.005(0.012)
nch0004	−0.023(0.034)	−0.029(0.029)	−0.039(0.035)	−0.042(0.030)
nch0511	−0.069***(0.026)	−0.063***(0.022)	−0.092***(0.027)	−0.081***(0.023)
nch1218	−0.029(0.021)	−0.026(0.018)	−0.037*(0.021)	−0.032*(0.018)
tcwork	0.004(0.039)	−0.004(0.033)	0.015(0.040)	0.008(0.034)
employer	−0.090*(0.051)	−0.070(0.043)	−0.115**(0.052)	−0.084*(0.044)
famly	−0.028(0.060)	−0.061(0.052)	−0.054(0.061)	−0.079(0.054)
ena	0.075**(0.032)	0.056**(0.026)	0.097***(0.033)	0.081***(0.027)
unemp	−0.092(0.127)	−0.035(0.086)	−0.056(0.130)	−0.014(0.089)
$h_1(1)$	−0.261***(0.042)	−0.241***(0.032)	−0.397***(0.070)	−0.355***(0.050)
$h_1(3)$	0.099***(0.017)	0.108***(0.014)	0.183***(0.029)	0.195***(0.023)
$h_1(4)$	0.365***(0.022)	0.365***(0.019)	0.623***(0.038)	0.612***(0.031)
$h_1(5)$	0.714***(0.045)	0.725***(0.038)	1.179***(0.077)	1.189***(0.061)
cut1	−0.149(1.196)	−1.718(0.635)	−0.104(2.092)	−2.044(0.879)
cut2	2.094(1.196)	0.478(0.635)	2.358(2.092)	0.359(0.879)
cut3	3.383(1.196)	1.779(0.635)	3.788(2.092)	1.793(0.879)
cut4	5.027(1.196)	3.371(0.635)	5.620(2.092)	3.556(0.879)
σ_u^2			0.276(0.014)	0.252(0.011)
Log likelihood	−27,735.7	−39,739.2	−27,175.4	−39,090.8

Notes: 1 Standard errors are in parentheses.
2 Levels of significance are 1%(***), 5%(**), and 10%(*), respectively.
3 Cuts 1-4 are the estimated cut points.

(ICC), $\rho=\sigma_u^2/(\sigma_u^2+1)$.[13] Estimated coefficients for initial period health observations are significant at 1%, which implies a positive correlation between the initial period health observation and unobserved latent health. Therefore, this indicates that it is necessary to control for SAH at the beginning of observations.

[13] This is slightly lower than 33% and 31% from Contoyannis *et al*. (2004) and 24%−32% (results from a pooled sample) from Ayllón and Blanco-Perez (2012).

Tables 6 and 7 present the estimated coefficients for state dependence and some explanatory variables for the Rabe-Hesketh method and the Contoyannis-Jones-Rice method, respectively. Although the differences are not highly significant, the Contoyannis-Jones-Rice method yields slightly greater magnitudes overall and we keep using the Rabe-Hesketh method to take account of possible biases.[14]

Table 6 A Comparison of Rabe-Hesketh to Contoyannis-Jones-Rice (men)

	Rabe		Jones	
	Unbalanced	Balanced	Unbalanced	Balanced
$h_{t-1}(1)$	−0.421***(0.033)	−0.473***(0.047)	−0.416***(0.034)	−0.472***(0.047)
$h_{t-1}(3)$	0.291***(0.017)	0.305***(0.021)	0.291***(0.017)	0.304***(0.021)
$h_{t-1}(4)$	0.695***(0.028)	0.674***(0.033)	0.698***(0.028)	0.675***(0.033)
$h_{t-1}(5)$	1.283***(0.056)	1.195***(0.071)	1.310***(0.056)	1.200***(0.071)
meanln (income)	−0.157***(0.020)	−0.237***(0.029)	−0.175***(0.019)	−0.236***(0.027)
middleschool	0.145***(0.024)	0.114***(0.031)	0.164***(0.024)	0.117***(0.031)
college	−0.001(0.033)	−0.005(0.045)	−0.001(0.032)	−0.011(0.045)
university	−0.041**(0.025)	−0.067***(0.034)	−0.043*(0.025)	−0.073**(0.034)
ena	0.297***(0.032)	0.465***(0.042)	0.310***(0.032)	0.468***(0.042)

Notes: 1 Standard errors are in parentheses.
2 Levels of significance are 1%(***), 5%(**), and 10%(*), respectively.

Table 7 A Comparison of Rabe-Hesketh to Contoyannis-Jones-Rice, women

	Rabe		Jones	
	Unbalanced	Balanced	Unbalanced	Balanced
$h_{t-1}(1)$	−0.391***(0.037)	−0.443***(0.049)	−0.388***(0.037)	−0.440***(0.049)
$h_{t-1}(3)$	0.289***(0.016)	0.280***(0.019)	0.289***(0.016)	0.281***(0.019)
$h_{t-1}(4)$	0.633***(0.024)	0.592***(0.028)	0.633***(0.024)	0.592***(0.028)
$h_{t-1}(5)$	1.146***(0.046)	1.146***(0.046)	1.152***(0.046)	1.070***(0.055)
meanln (income)	−0.188***(0.018)	−0.244***(0.025)	−0.198***(0.017)	−0.237***(0.024)
middleschool	0.215***(0.027)	0.212***(0.034)	0.218***(0.027)	0.220***(0.034)
single	0.210***(0.068)	0.197**(0.090)	0.210***(0.067)	0.201**(0.089)
nch0511	−0.081**(0.023)	−0.092***(0.027)	−0.084*(0.023)	−0.093**(0.027)
ena	0.081***(0.033)	0.097***(0.033)	0.082***(0.027)	0.100***(0.033)

Notes: 1 Standard errors are in parentheses.
2 Levels of significance are 1%(***), 5%(**), and 10%(*), respectively.

The results concerning the set of explanatory variables included to control for observed heterogeneity are now discussed. For the estimation of preferred random effects specifications, estimated coefficients of a few explanatory variables are significant. As shown in Tables 8 and 9, estimated coefficients of much more explanatory variables are significant without controlling for state dependence and unobserved heterogeneity, and solving for initial conditions problem. However, when these elements are sequentially controlled for, the significance of most disappears. As Ayllón and Blanco-Perez (2012) point out, these results may suggest that the effects of observed heterogeneity on SAH are generally overestimated because they capture the

[14] Needless to say, the fact that the outcomes between two methods in this practice are not so substantial does not guarantee that the Contoyannis-Jones-Rice method is the right approach.

TABLE 8 VARIOUS MODEL SPECIFICATIONS (UNBALANCEDPANEL; MEN)

	Baseline	Dynamic	No Wooldridge	Wooldridge
$h_{t-1}(1)$		−0.681***(0.030)	−0.455***(0.033)	−0.421***(0.033)
$h_{t-1}(3)$		0.535***(0.015)	0.340***(0.017)	0.291***(0.017)
$h_{t-1}(4)$		1.286***(0.022)	0.878***(0.028)	0.695***(0.028)
$h_{t-1}(5)$		2.222***(0.046)	1.646***(0.055)	1.283***(0.056)
ln (income)	−0.115***(0.006)	−0.079***(0.007)	−0.074***(0.008)	−0.019**(0.009)
meanln (income)				−0.157***(0.020)
age	0.291***(0.024)	0.202***(0.029)	0.235***(0.038)	0.025(0.062)
age2	−0.656***(0.079)	−0.466***(0.093)	−0.531***(0.122)	0.057(0.203)
age3	0.669***(0.106)	0.488***(0.123)	0.545***(0.163)	−0.234(0.279)
age4	−0.242***(0.051)	−0.183***(0.058)	−0.197**(0.078)	0.191(0.136)
single	0.112***(0.025)	0.059**(0.028)	0.061(0.037)	−0.048(0.064)
div/sep	0.261***(0.029)	0.164***(0.033)	0.216***(0.045)	0.101(0.079)
widow	−0.180***(0.038)	−0.132***(0.041)	−0.149***(0.058)	0.065(0.110)
middleschool	0.301***(0.015)	0.179***(0.016)	0.269***(0.024)	0.145***(0.024)
college	−0.018(0.020)	−0.025(0.023)	−0.027(0.033)	−0.001(0.033)
university	−0.114***(0.015)	−0.087***(0.017)	−0.011***(0.024)	−0.041*(0.025)
hhsize	−0.019***(0.006)	−0.014**(0.006)	−0.020**(0.008)	−0.023*(0.013)
nch0004	0.075***(0.018)	0.035*(0.020)	0.052**(0.024)	0.060*(0.031)
nch0511	0.025**(0.012)	0.009(0.013)	0.015(0.017)	0.026(0.024)
nch1218	0.014(0.010)	0.004(0.012)	0.008(0.014)	0.020(0.020)
tcwork	0.090***(0.020)	0.073***(0.022)	0.066**(0.028)	−0.053(0.037)
employer	0.054***(0.015)	0.059***(0.017)	0.047**(0.023)	−0.047(0.036)
family	0.094*(0.056)	0.042(0.063)	0.041(0.079)	−0.065(0.103)
ena	0.530***(0.018)	0.374***(0.020)	0.447***(0.025)	0.297***(0.032)
unemp	0.116***(0.040)	0.043(0.047)	0.071(0.051)	−0.009(0.056)
$h_1(1)$				−0.247***(0.041)
$h_1(3)$				0.228***(0.022)
$h_1(4)$				0.699***(0.034)
$h_1(5)$				1.110***(0.071)
cut1			1.530(0.429)	−0.463(0.838)
cut2			3.919(0.429)	1.938(0.838)
cut3			5.248(0.430)	3.293(0.838)
cut4			6.752(0.431)	4.856(0.838)
σ_u^2			0.214(0.012)	0.195(0.010)
Log likelihood	−45,130.0	−34,160.9	−33,835.0	−33,304.2

Notes: 1 Standard errors are in parentheses.
2 Levels of significance are 1%(***), 5%(**), and 10%(*), respectively.
3 Cuts 1-4 are the estimated cut points.
4 The baseline is the model without state dependence and random effects. The dynamic model is the baseline model with state dependence. No wooldridge is the model formed by adding random effects to the dynamic model. Wooldridge is the model with the Woodridge solution as specified in the paper.

impact that should be attributed to previous health or other unobserved variables not present in most data sets. For the educational attainment[15], the middle school degree negatively affects the health status for both men and women (baseline category = a high school degree). For men, the university degree is highly significant, but it is not for women.[16] Being single has a

[15] It is more precise to state that these variables measure the effects of graduating from school, not the effects of schooling.

TABLE 9 VARIOUS MODEL SPECIFICATIONS (UNBALANCEDPANEL; WOMEN)

	Baseline	Dynamic	No	Wooldridge
$h_{t-1}(1)$		−0.728***(0.033)	−0.436***(0.037)	−0.391***(0.037)
$h_{t-1}(3)$		0.559***(0.014)	0.328***(0.016)	0.289***(0.016)
$h_{t-1}(4)$		1.276***(0.019)	0.771***(0.024)	0.633***(0.024)
$h_{t-1}(5)$		2.172***(0.037)	1.408***(0.046)	1.146***(0.046)
ln (income)	−0.113***(0.005)	−0.080***(0.006)	−0.072***(0.007)	−0.015*(0.008)
meanln (income)				−0.188***(0.018)
age	0.215***(0.022)	0.125***(0.027)	0.183***(0.036)	0.035(0.054)
age2	−0.578***(0.070)	−0.327***(0.082)	−0.497***(0.113)	−0.046(0.175)
age3	0.748***(0.091)	0.419***(0.107)	0.652***(0.147)	−0.023(0.234)
age4	−0.346***(0.042)	−0.193***(0.049)	−0.303***(0.068)	0.049(0.111)
single	0.153***(0.027)	0.108***(0.031)	0.131***(0.043)	0.210***(0.068)
div/sep	0.309***(0.029)	0.196***(0.031)	0.258***(0.046)	0.118(0.079)
widow	0.163***(0.019)	0.102***(0.020)	0.149***(0.031)	0.078(0.060)
middleschool	0.342***(0.015)	0.221***(0.017)	0.346***(0.027)	0.215***(0.027)
college	−0.045**(0.020)	−0.037*(0.022)	−0.049(0.033)	0.014(0.033)
university	−0.089***(0.018)	−0.055***(0.020)	−0.077***(0.029)	0.033(0.030)
hhsize	−0.034***(0.005)	−0.021***(0.006)	−0.018**(0.008)	0.005(0.012)
nch0004	−0.007(0.017)	−0.0001(0.019)	−0.011(0.024)	−0.042(0.030)
nch0511	−0.006(0.011)	−0.005(0.013)	−0.028*(0.017)	−0.081***(0.023)
nch1218	0.005(0.009)	0.006(0.011)	−0.006(0.014)	−0.032*(0.018)
tcwork	0.065***(0.021)	0.027(0.023)	0.030(0.028)	0.008(0.034)
employer	0.001(0.021)	−0.004(0.023)	−0.036(0.032)	−0.084*(0.044)
family	0.056**(0.024)	0.050*(0.026)	0.027(0.036)	−0.079(0.054)
ena	0.193***(0.014)	0.110***(0.016)	0.135***(0.021)	0.081***(0.027)
unemp	0.128**(0.065)	0.001(0.076)	0.027(0.083)	−0.014(0.089)
$h_1(1)$				−0.355***(0.050)
$h_1(3)$				0.195***(0.023)
$h_1(4)$				0.612***(0.031)
$h_1(5)$				1.189***(0.061)
cut1			0.280(0.423)	−2.044(0.879)
cut2			2.671(0.424)	0.359(0.879)
cut3			4.085(0.424)	1.793(0.879)
cut4			5.804(0.425)	3.556(0.879)
σ_u^2			0.279(0.013)	0.252(0.011)
Log likelihood	−52,109.5	−40,248.2	−39,659.4	−39,090.8

Notes: 1 Standard errors are in parentheses.
2 Levels of significance are 1%(***), 5%(**), and 10%(*), respectively.
3 Cuts 1-4 are the estimated cut points.
4 The baseline is the model without state dependence and random effects. The dynamic model is the baseline model with state dependence. No wooldridge is the model formed by adding random effects to the dynamic model. Wooldridge is the model with the Woodridge solution as specified in the paper.

significant negative effect on the health status of women, whereas the marital status has no effect on that of men. The number of children aged 5−11 affects women's health positively, while it is not significant for men. With respect to the work status, those who are not economically active tend to have negative individual health in comparison to those with

[16] Estimated coefficients for a college degree are not significant in most cases. This may reflect the perceived equivalence of a college degree to high school graduation in Korea.

permanent contracts for both men and women. The logarithm for equivalized household income is generally significant for only men, and its average is significant at 1% in all specifications for both men and women. This may suggest that a proxy for permanent income is more relevant for individual health than current income, even after controlling for state dependence.[17]

In addition to detecting the presence of state dependence in SAH, an interesting research topic is to investigate the magnitude and degree of state dependence with respect to individual characteristics. To present an indication of the magnitude of relationships between SAH and explanatory variables, average partial effects are calculated (Table 10). It is obviously possible to compute average partial effects for each of the five categories of SAH. However, for parsimony, average partial effects of state dependence, income, and educational attainment on the probability of reporting excellent health are reported. In addition, only those results for random effects models are presented. First, men exhibit stronger state dependence than women. Numbers in square bracket are estimated coefficients for state dependence from Contoyannis *et al*. (2004). Although it is not directly comparable, state dependence in health evolution in the UK appears to be much stronger than that in Korea. Mean income effects are greater for men than for women, and the middle school degree has similar effects for both men and women.

TABLE 10 AVERAGE PARTIAL EFFECTS ON THE PROBABILITY OF REPORTING EXCELLENT HEALTH FOR SELECTED VARIABLES

	Men		Women	
	Balanced	Unbalanced	Balanced	Unbalanced
$h_{t-1}(1)$	0.025***(0.003)	0.028***(0.002)	0.017***(0.002)	0.018***(0.002)
	[0.082]	[0.085]	[0.082]	[0.074]
$h_{t-1}(3)$	−0.016***(0.001)	−0.020***(0.001)	−0.011***(0.001)	−0.013***(0.001)
	[−0.080]	[−0.077]	[−0.064]	[−0.061]
$h_{t-1}(4)$	−0.035***(0.002)	−0.047***(0.002)	−0.022***(0.001)	−0.029***(0.001)
	[−0.151]	[−0.145]	[−0.121]	[−0.118]
$h_{t-1}(5)$	−0.062***(0.005)	−0.087***(0.005)	−0.040***(0.003)	−0.052***(0.003)
	[−0.184]	[−0.179]	[−0.144]	[−0.144]
meanln (income)	0.012***(0.002)	0.011**(0.001)	0.009***(0.001)	0.009***(0.001)
middleschool	−0.006***(0.002)	−0.010***(0.002)	−0.008***(0.001)	−0.010***(0.001)
college	0.0003(0.002)	0.00004(0.002)	0.00005(0.002)	−0.001(0.001)
university	0.003**(0.002)	0.003**(0.002)	−0.001(0.002)	−0.001(0.001)

Notes: 1 Standard errors are in parentheses.
2 Levels of significance are 1%(***), 5%(**), and 10%(*), respectively.

Further, state dependence may be influenced by age, income, educational attainment, and initial health.[18] To investigate this, the samples of males and females are divided into subsamples based on age ($\leq$ 45 and $>$ 45) in the first wave, income quintiles, educational attainment, and initial health. For the subsample analyses by educational attainment, the sample is limited to adults 25 years old or older because otherwise the current students are categorized

[17] See Frijters *et al*. (2003) and Case *et al*. (2002), who interpret current income as a measure of transitory income shocks and mean income as a measure of long-term or permanent income.

[18] For instance, previous studies have found that negative effects of health shocks remain longer for children from lower income households. See Currie and Hyson (1999) and Currie and Stabile (2003).

to lower educational attainment than the expected final educational attainment. For each subsample, the dynamic random effects ordered probit model specified in Section 3 is estimated (Tables 11-14). Table 11 shows that the magnitude of the state dependence effects is clearly lower for older individuals. As shown in Table 12, there is a clear pattern for educational attainment for women. Comparing “middle” with “high”, and “high” with “university”, clearly the magnitude of state dependence is larger for individuals with higher educational attainment for this group. With respect to equivalized household income quintiles, Table 13 also shows some patterns. By comparing the first group with the second group, and the second with the third, the magnitude of state dependence becomes larger for individuals with higher income for both genders. Finally, Table 14 clearly shows that the effect of state dependence strengthens with the deterioration of initial health status.

Table 11 Average Partial Effects on the Probability of Reporting Excellent Health by Age Group

	Men		Women	
	<=45	>45	<=45	>45
$h_{t-1}(1)$	0.042***	0.008***	0.031***	0.003**
$h_{t-1}(3)$	−0.029***	−0.007***	−0.025***	−0.002***
$h_{t-1}(4)$	−0.072***	−0.017***	−0.055***	−0.005***
$h_{t-1}(5)$	−0.136***	−0.032***	−0.095***	−0.011***

Notes: 1 Levels of significance are 1%(***), 5%(**), and 10%(*), respectively.

Table 12 Average Partial Effects on the Probability of Reporting Excellent Health by Educational Attainment

	Men				Women			
	Middle	High	College	University	Middle	High	College	University
$h_{t-1}(1)$	0.004	0.030***	0.016*	0.043***	0.002*	0.023***	0.016**	0.056***
$h_{t-1}(3)$	−0.006***	−0.019***	−0.031***	−0.024***	−0.002***	−0.016***	−0.030***	−0.035***
$h_{t-1}(4)$	−0.015***	−0.044***	−0.075***	−0.057***	−0.006***	−0.037***	−0.060***	−0.085***
$h_{t-1}(5)$	−0.028***	−0.092***	−0.077**	−0.065***	−0.011***	−0.067***	−0.086***	−0.240***

Notes: 1 Levels of significance are 1%(***), 5%(**), and 10%(*), respectively.

Table 13 Average Partial Effects on the Probability of Reporting Excellent Health by Equivalized Household Income Quintile

	Men					Women				
	1st quintile (20%)	2nd quintile (40%)	3rd quintile (60%)	4th quintile (80%)	5th quintile (100%)	1st quintile (20%)	2nd quintile (40%)	3rd quintile (60%)	4th quintile (80%)	5th quintile (100%)
$h_{t-1}(1)$	0.022***	0.033***	0.050***	0.036***	0.052***	0.009***	0.030***	0.036***	0.029***	0.039***
$h_{t-1}(3)$	−0.015***	−0.019***	−0.037***	−0.038***	−0.034***	−0.007***	−0.021***	−0.026***	−0.031***	−0.024***
$h_{t-1}(4)$	−0.033***	−0.056***	−0.085***	−0.070***	−0.082***	−0.016***	−0.047***	−0.058***	−0.065***	−0.059***
$h_{t-1}(5)$	−0.058***	−0.108***	−0.140***	−0.126***	−0.119***	−0.029***	−0.082***	−0.100***	−0.127***	−0.094***

Notes: 1 Levels of significance are 1%(***), 5%(**), and 10%(*), respectively.

Table 14 Average Partial Effects on the Probability of Reporting Excellent Health by Initial Health Status

	Men					Women				
	Very poor	Poor	Fair	Good	Excellent	Very poor	Poor	Fair	Good	Excellent
$h_{t-1}(1)$	0.068***	0.034***	0.015***	0.005**	0.016	0.058***	0.027***	0.005**	0.004**	−
$h_{t-1}(3)$	−0.019	−0.024***	−0.011***	−0.001*	−0.001	−0.036*	−0.017***	−0.009***	−0.001***	−
$h_{t-1}(4)$	−0.118***	−0.051***	−0.030***	−0.005***	−0.004	−0.106**	−0.037***	−0.018***	−0.004***	−
$h_{t-1}(5)$	−0.408***	−0.118***	−0.048***	−0.010***	−0.007*	−0.517**	−0.055***	−0.034***	−0.008***	−

Notes: 1 Levels of significance are 1%(***), 5%(**), and 10%(*), respectively.

From the subsample analyses, we can see that the magnitude of state dependence varies with individual characteristics in some subgroups. There are several determinants of state dependence, such as reporting consistency, frequency of negative health shocks, and recuperative power. Those who are better educated and have higher income are likely to face less frequent negative health schocks and have stronger recuperative power. However, the results from subsample analyses show the opposite phenomena. Reporting heterogeneity happens if subgroups of the population use systematically different cut point levels when reporting their SAH, depite having the same level of true health as presented in Contoyannis *et al*. (2004). In this respect, we tentatively presume that the variations of state dependence across some subsamples may be originated from the reporting heterogeneity of SAH.

V. *Robustness*

1. Attrition Bias

As presented in Jones *et al*. (2006) and Jones *et al*. (2013), using panel data to analyze longitudinal models of health entails a risk that the result may be contaminated by a bias associated with longitudinal non-response. There are dropouts from panels in each wave, and some of these may be related directly to health problems such as death, serious illness, and moving into institutional care. As a result, long-term survivors who remain in the panel are likely to be healthier on average compared to the sample at wave 1. The health of survivors tends to be better than the population as a whole, and their rate of decline in health tends to be lower. Failing to account for the non-response may result in an attrition bias in the empirical model of SAH. To test for this attrition bias, the simple variable addition test proposed in Verbeek and Nijman (1992) is conducted. Test variables for the test include (1) the number of waves individual i participates in the panel, (2) a 0−1 variable equal to 1 if and only if individual i is observed in all periods and (3) an indicator for whether individual i is in the subsequent period. It should be noted that the variable addition test may have low power, as shown in Nicoletti (2006). For this reason, a strategy based on the inverse probability weighted (IPW) estimator,[19], an approach to obtain consistent estimator in the presence of nonrandom

[19] For further details such as assumptions and statistical properties of the estimator, the reader is referred to Wooldridge (2002b) and, for more general settings, to Wooldridge (2007).

selection, is employed. This method is applied to the pooled ordered probit. To implement this estimation method, we estimate probit equations for the response ($d_{it}=1$) versus non-response ($d_{it}=0$) at each wave, $t=2, ..., 10$, conditional on a set of covariates (z_{i1}) that are measured for all individuals in the first wave. This relies on the selection on observables and implies that non-response can be treated as ignorable non-response conditional on z_{i1}. In practice, z_{i1} includes initial values of all regressors in equation (1). Further, it includes initial values of SAH and other indicators of morbidity.[20] In addition, z_{i1} includes initial values of individuals' activity status.[21] The inverse of the fitted probability from these models[22], $1/\hat{p}_{it}$, is used to weight observations in the maximum likelihood estimation of the pooled ordered probit model as follows:

$$\log L=\sum_{i}^{n}\sum_{t}^{T}(d_{it}/\hat{p}_{it})\log L_{it} \tag{6}$$

Table 15 presents the results from the variable addition test for attrition bias estimated using the dynamic ordered probit model with the Wooldridge solution. All test variables show no evidence of any attrition bias for men, whereas all coefficients are negative and significant for women. This reflects that response rates may be positively related to health in the female sub-sample. Therefore, attrition bias seems very unlikely to occur for men in the sample but likely for women.

TABLE 15 VERBEEK AND NIJMAN TESTS FOR ATTRITION BIAS

	Men	Women
All waves	0.011(0.022)	−0.045**(0.022)
Subsequent waves	−0.001(0.074)	−0.097***(0.037)
Number of responses	−0.006(0.008)	−0.021**(0.009)

Table 16 shows the results for the IPW estimation described in (6). It may seem to be surprising that for major variables such as lagged health status, income, and initial health status the differences between the coefficients from non-IPW estimation and IPW estimation are trivial. However, this may suggest that longitudianl non-response does not play a significant role and, as a result, it does not bias the estimates of coefficients for major variables.

[20] For instance, whether an individual reports a restrictive physical conditions and whether an individual has experienced or is experiencing at critical disease such as cancer, high blood pressure, and diabetes.

[21] There are eight categories for this status: mainly working, mainly doing housework and working a bit, mainly studying and working a bit, mainly doing something else and working a bit, doing housework only, caring for children only, studying only, and no work.

[22] The results for the estimation of probit models are not reported in the paper and available from the author upon request.

Table 16 Pooled Ordered Probit Using Inverse Probability Weights

	Men (NT=35,346)	Women (NT=40,560)
$h_{t-1}(1)$	−0.633***(0.038)	−0.662***(0.043)
$h_{t-1}(3)$	0.475***(0.015)	0.513***(0.015)
$h_{t-1}(4)$	1.079***(0.027)	1.120***(0.022)
$h_{t-1}(5)$	1.836***(0.059)	1.866***(0.046)
ln (income)	−0.012(0.009)	−0.009(0.008)
meanln (income)	−0.133***(0.016)	−0.142***(0.014)
age	−0.019(0.065)	0.018(0.057)
age2	0.183(0.218)	−0.014(0.189)
age3	−0.385(0.306)	−0.034(0.262)
age4	0.252*(0.152)	0.042(0.128)
single	−0.049(0.060)	0.184***(0.064)
div/sep	0.082(0.077)	0.096(0.080)
widow	0.018(0.114)	0.036(0.060)
middleschool	0.117***(0.017)	0.170***(0.018)
college	−0.011(0.022)	−0.005(0.022)
university	−0.048***(0.018)	0.002(0.020)
hhsize	−0.023*(0.013)	0.005(0.012)
nch0004	0.049(0.031)	−0.026(0.029)
nch0511	0.018(0.023)	−0.062***(0.022)
nch1218	0.013(0.019)	−0.028*(0.017)
tcwork	−0.052(0.038)	−0.008(0.033)
employer	−0.048(0.037)	−0.072*(0.043)
family	−0.061(0.105)	−0.067(0.053)
ena	0.214***(0.034)	0.035(0.026)
unemp	−0.031(0.059)	−0.028(0.089)
$h_1(1)$	−0.169***(0.032)	−0.232***(0.037)
$h_1(3)$	0.144***(0.015)	0.110***(0.014)
$h_1(4)$	0.473***(0.025)	0.373***(0.020)
$h_1(5)$	0.740***(0.055)	0.712***(0.043)
cut1	−0.509(0.765)	−2.976(0.843)
cut2	1.712(0.765)	−0.779(0.845)
cut3	2.961(0.765)	0.521(0.845)
cut4	4.396(0.764)	2.102(0.845)
Log likelihood	−43,645.4	−51,132.0

Notes: 1 Standard errors are in parentheses.
2 Levels of significance are 1%(***), 5%(**), and 10%(*), respectively.
3 Cuts 1-4 are the estimated cut points.

2. Measurement Errors in Self-assessed Health

To investigate the consistency in reporting SAH, the method adopted in Vaillant and Wolff (2012) is used. In the KLIPS data set, there is a retrospective question about the evolution of health since last year in addition to the question about the current health status. That is, the respondent in the survey should assess whether his or her health is “much better”, “better”, “more or less the same”, “worse”, or “much worse” in comparison to the previous year’s health. This information is used to investigate whether answers of respondents to this question are consistent with changes between two consecutive years in SAH. In practice, "much better" is merged with "better" and "much worse" with "worse". As a result, there are three categorical variables (baseline category = "more or less the same"), and these variables are used in the random effects ordered probit specification to estimate the SAH model.

$$h_{it}^{*} = \beta' x_{it} + \gamma_1 \cdot better + \gamma_2 \cdot worse + \alpha_i + \epsilon_{it} \; (i=1, \ldots, N; t=2, \ldots, T_i), \tag{7}$$

where x_{it} is a set of observed explanatory variables that are the same as those in Model (1). The idea is as follows. For instance, a respondent answers good health in both 2010 and 2011. If the respondent's answers are consistent, then he or she should indicate that in 2011, as compared to 2010, his or her SAH is "more or less the same". Further, if he or she reports "fair" in 2012, then he or she should answer in that period that his or her health has worsened since 2011 to be consistent. Under this framework, it is claimed that if there is no measurement error in reporting SAH, estimated coefficients for γ_1 and γ_2 should be negative and positive, respectively. The results in Table 17 verify these expectations under the presence of consistency in reporting by respondents. That is, it is shown that individuals whose SAH is worse in t than in $t-1$ are more likely to report that their health has deteriorated since the previous year, whereas those with a better SAH outcome in t than in $t-1$ are more likely to state that their health status has improved in comparison to the previous year.

However, although strong relationship indicates consistent reporting by a majority of respondents, it does not quantify the magnitude of the reporting error. For this, Tables 18 and 19 present the number of respondents who report improvement (deterioration) in health for those whose SAH improves (deteriorates) since the previous survey. With the use of the retrospective answer, 84% of male respondents and 79% of female respondents indicate that their health remains more or less the same as the previous period. However, by comparing SAH between t and $t-1$, 58% of men and 56% of women answer the same SAH in both periods. As pointed out in Vaillant and Wolff (2012), this discrepancy may be caused by the inaccuracy of the definition of "more or less the same" health since the previous year. That is, answers become more consistent if respondents report that SAH either improves or deteriorates since the previous year. For instance, for men answering that SAH has deteriorated since the previous year, 46% indeed indicate poorer SAH in t than in $t-1$, whereas 11% report better health in t. Similarly, in the case of the better health since the previous year, 26% of male respondents report better health in t than in $t-1$, and 57% report the more or less the same SAH. However, a significant proportion of male respondents reports poorer SAH (18%).[23] Therefore, although there is evidence of overall reporting consistency, it should be noted that there is still a non-negligible portion of respondents inconsistently reporting SAH.

[23] Female respondents show similar patterns.

Table 17 Random Effects Ordered Probit Models of Health Using Health Evolution Since Last Year

	Men		Women	
	Balanced NT=22,401	Unbalanced NT=35,346	Balanced NT=28,296	Unbalanced NT=40,560
ln (income)	−0.066***(0.013)	−0.076***(0.010)	−0.073***(0.011)	−0.075***(0.009)
age	0.259***(0.089)	0.293***(0.046)	0.163***(0.064)	0.194***(0.043)
age2	−0.741***(0.265)	−0.825***(0.146)	−0.529***(0.197)	−0.626***(0.132)
age3	0.894***(0.334)	0.992***(0.195)	0.739***(0.254)	0.881***(0.171)
age4	−0.370**(0.152)	−0.409***(0.092)	−0.348***(0.118)	−0.421***(0.079)
single	−0.028(0.060)	−0.056(0.045)	0.079(0.069)	0.075(0.050)
div/sep	0.213***(0.069)	0.214***(0.053)	0.277***(0.063)	0.259(0.052)***
widow	−0.0002(0.083)	−0.080(0.067)	0.145***(0.04)	0.119***(0.035)
middleschool	0.215***(0.035)	0.281***(0.028)	0.371***(0.036)	0.338***(0.030)
college	−0.135***(0.051)	−0.105***(0.039)	−0.073(0.049)	−0.082**(0.038)
university	−0.131***(0.038)	−0.070**(0.029)	−0.121***(0.045)	−0.122***(0.034)
hhsize	0.003(0.014)	−0.006(0.010)	−0.026**(0.011)	−0.031***(0.009)
nch0004	0.018(0.038)	0.011(0.030)	0.057(0.035)	0.047(0.029)
nch0511	−0.004(0.026)	−0.011(0.021)	0.034(0.024)	0.025(0.020)
nch1218	−0.001(0.023)	−0.002(0.018)	0.023(0.020)	0.021(0.017)
tcwork	0.077*(0.043)	0.023(0.035)	0.009(0.041)	0.015(0.035)
employer	0.153***(0.033)	0.102***(0.027)	0.059(0.044)	0.017(0.038)
family	−0.026(0.115)	−0.006(0.098)	0.112**(0.049)	0.075*(0.043)
ena	0.445***(0.040)	0.424***(0.031)	0.175***(0.031)	0.157***(0.025)
unemp	0.141(0.091)	0.212***(0.067)	0.105(0.158)	0.120(0.106)
SAH in t better than in $t-1$	−0.224***(0.027)	−0.241***(0.022)	−0.412***(0.023)	−0.406***(0.020)
SAH in t worse than in $t-1$	0.585***(0.026)	0.557***(0.021)	0.582***(0.022)	0.573***(0.019)
cut1	1.180(1.097)	1.555(0.520)	−0.319(0.765)	−0.035(0.500)
cut2	4.599(1.098)	5.042(0.521)	3.082(0.765)	3.416(0.501)
σ_u^2	0.218(0.014)	0.225(0.012)	0.257(0.014)	0.253(0.011)
Log likelihood	−10,736.3	−16,533.5	−14,472.2	−20,369.6

Notes: 1 Standard errors are in parentheses.
2 Levels of significance are 1%(***), 5%(**), and 10%(*), respectively.
3 Cuts 1-4 are the estimated cut points.

Table 18 Health Transitions and Retrospective Answer (unbalance panel; men)

		Retrospective			No. of obs.
		Worse	The same	Better	
Transition between t and $t-1$	Worse	1,872	5,503	295	7,670
	The same	1,734	17,647	945	20,326
	Better	462	6,462	426	7,350
	No. of obs	4,068	29,612	1,666	35,346

TABLE 19 HEALTH TRANSITIONSAND RETROSPECTIVE ANSWER (UNBALANCED PANEL; WOMEN)

		Retrospective			No. of obs.
		Worse	The same	Better	
Transition between t and $t-1$	Worse	2,792	5,943	228	8,963
	The same	3,187	18,725	844	22,756
	Better	783	7,526	532	8,841
	No. of obs	6,762	32,194	1,604	40,560

VI. *Discussion*

This paper investigates the determinants of individual health dynamics using KLIPS data. In particular, the paper examines how state dependence, unobserved heterogeneity, and observed heterogeneity jointly affect overall health evolution. There is persistence in health evolution, as shown in the description of health measured by SAH in Korea, and therefore it becomes fundamental to identify true state dependence after controlling for unobserved heterogeneity across individuals. For this purpose, a dynamic random effects ordered probit model that solves the initial conditions problem using the Wooldridge solution is estimated. The estimation results show persistence in health dynamics characterized by significant positive state dependence and unobserved heterogeneity across individuals. Therefore, those who fall into a poor health status because of health shocks are not likely to leave this negative health status. On the other hand, individual unobserved heterogeneity accounts for approximately 20% of the unexplained variation in health. Previous health studies have emphasized that observed heterogeneity measured by socioeconomic variables plays an important role in determining individual health and its evolution. However, consistent with the findings of Contoyannis *et al.* (2004) and Ayllón and Blanco-Perez (2012), many socioeconomic variables lose their explanatory power once state dependence and unobserved heterogeneity are controlled for. This suggests that coefficients of socioeconomic variables except for household income and educational attainment tend to be overestimated unless these two factors are appropriately controlled for. Two robustness checks are performed to strengthen the empirical results. First, the presence of some attrition bias is detected for at least the sub-samples based on the simple test. Therefore, an empirical model augmented with inverse probability weights is estimated. However, qualitative features of the estimation results are not different from those without the IPW. Therefore, although some attrition exists due to the longitudinal non-response, the resluts suggest that it does not influence the magnitude of estimated effects of state dependence and socioeconomic variables. Second, the reliabity of SAH is evaluated to consider whether there is a measurement error in reporting the individual subjective health status. For this, a random effects ordered probit model using the retrospective health status variable is estimated to determine consistency in reporting by respondents. Although the results indicate that the overall measurement error may not be likely at least from regression analysis, it is necessary to note that there is still some small portion of respondents reporting inconsistenly. The presence of genuine state dependence implies that a short-term health economic policy intervening to improve health may have long-term effects on health. Ultimately, this conclusion suggets a need for further research on how child health can be determined in a more detailed and systematic manner because individual characteristics traced back to early adulthood and before can have considerable influence on individual health over the whole life cycle, as pointed out in Halliday (2008).[24]

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[24] Suggestion in Ayllón and Blanco-Perez (2012) to include childhood characteristics and environments as proxies for individual heterogeneity seems to be related to this concern.

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